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IMPACT OF CLIMATE CHANGE ON FUTURE AVAILABILITY OF WATER FOR IRRIGATION AND HYDROPOWER GENERATION IN OMO-GIBE BASIN, ETHIOPIA

TAMIRU PAULOS ORKODJO

MARCH, 2023

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IMPACT OF CLIMATE CHANGE ON FUTURE AVAILABILITY OF WATER FOR IRRIGATION AND HYDROPOWER GENERATION IN OMO-GIBE BASIN, ETHIOPIA

BY

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MSc. Hydrology and Water Resource Management

(UDS/DID/0012/19)

A THESIS SUBMITTED TO THE DEPARTMENT OF AGRICULTURAL ENGINEERING, SCHOOL OF ENGINEERING, UNIVERSITY FOR DEVELOPMENT STUDIES, TAMALE, GHANA

IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF DOCTOR OF PHILOSOPHY (PhD) IN IRRIGATION AND DRAINAGE ENGINEERING

MARCH, 2023

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DECLARATION

I, hereby, declare that this thesis is the result of my own original work towards the award of a Doctor of Philosophy (PhD) and that no part of it has been presented for a degree in this University or elsewhere. The work of others, which served as sources of information for this study, has been duly acknowledged in the form of references.

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I hereby declare that the preparation and presentation of the thesis was supervised following the guidelines on the supervision of the thesis laid down by the University for Development Studies.

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ABSTRACT

Impacts of climate change could change how much water is available in the future for various uses. This study objective was to project the impacts of climate change and identify adaptation measures in order to increase the amount of water that will be available for irrigation and hydropower generation in the future. Climate change was projected using multi-model Regional Climate Change Models (RCMs) Coordinated Regional Climate Downscaling Experiment (CORDEX)-Africa models under two climate change emission scenarios RCP 4.5 and RCP 8.5.Future water availability magnitude, allocation, and demand for irrigation and hydropower generation were projected using an integrated approach using Soil and Water Assessment Tool (SWAT) and Water Evaluation and Planning (WEAP) hydrological models. Climate change was projected in three (3) windows: short-term (2017 - 2044), medium-term (2045 - 2072), and long-term (2073 - 2100) were compared to the reference period (1987 – 2019). Mann-Kendall (MK) trend testing was used to determine if a change is statistically significant and to detect trends in temperature, precipitation, and streamflow. Significantly positive (rising) changes in temperature were predicted by emission scenarios under RCP4.5 and RCP8.5, but significantly negative (declining) changes in precipitation and streamflow. The projected annual average temperature increases were 2.41°C and 4.5°C under the RCP4.5 and RCP8.5 emission scenarios, respectively. The projected average annual decrease in precipitation and streamflow ranged from 10.7 % to 13.6 % and 11.1 % to 13.8 % and; 7.0 % to 10.9 % and 10.9 % to 12.8 % under the RCP4.5 and RCP8.5 emission scenarios respectively. The impact of climate change could lead to an 8.0 % to 25.1 % increase in future water shortages. As a result, water shortages for irrigation could increase by 15.5 - 25.4 % and hydropower generation by 10.5 - 20.2 % during the study periods 2017-2100. Under the combined effect of climate change and rising water demand, the increase in variation in water shortage ranges from 7.9 % to 30.6 %. Quantified and projected climate change impacts statistics showed that the future availability of water for irrigation and hydroelectric power generation will decrease in the future. In this study, two climate change adaptation options were identified to be effective in managing future water supply and demand sides and ensuring future water availability for irrigation and hydropower generation. The results of the study indicated that more research is needed to determine whether these options for coping with climate change are appropriate for potential climatic scenarios in the Omo-Gibe River basin.

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Finally, I would like to give a very big thank you to my wife Betelihem Erbalo Wote. I would also like to express sincere gratitude to my mother, and brothers, and a special one goes to my little sister Melikm, friends, and everyone that has prayed to God, helped, and supported me through this process.

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DEDICATION

This work is warm-heartedly dedicated to my wife and children.

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LIST OF ACRONYMS AND ABBREVIATIONS

Acronym	Meaning
BM^3	Billion cubic meters
°C	Centigrade
CO_2	Carbon dioxide
SCS-CN	Soil Conservation Service Curve Number
CMIP	Coupled Model Intercomparison Project
CMIP3	Coupled Model Intercomparison Project Phase 3
CMIP5	Coupled Model Intercomparison Project Phase 5
CORDEX	Coordinated Regional Climate Downscaling Experiment
CSA	Central Statistics Agency of Ethiopia
CUP	Calibration and Uncertainty Programs
DEM	Digital Elevation Model
IDSDAA	Irrigation Development and Schemes Administration Agency
EEPCO	Ethiopian Electric Power Corporation
FAO	Food Organization Association
GCMs	General Circulation Models
GHGs	Greenhouse gases
GLUE	General Probability Uncertainty Estimation
GIS	Geographic Information System
GWP	Global Water Partnership
IHA	Indicators of Hydrologic Alteration
HEC-HMS	Hydrologic Engineering Center-Hydrologic Modeling System
H0	Null Hypothesis
HRUs	Hydrological response units
HSPF	Hydrologic Simulation Program-FORTRAN
IR	Industrial Revolution
IPCC	Intergovernmental Panel on Climate Change

IPCC AR1	Intergovernmental Panel on Climate Change First Assessment Report
IPCC AR2	Intergovernmental Panel on Climate Change Second Assessment Report
IPCC AR3	Intergovernmental Panel on Climate Change Third Assessment Report
IPCC AR4	Intergovernmental Panel on Climate Change Fourth Assessment Report
IPCC AR5	Intergovernmental Panel on Climate Change Fifth Assessment Report
IPCC AR6	Intergovernmental Panel on Climate Change Sixth Assessment Report
IWRM	Integrated water resource management
IWMI	International Water Management Institute
km^2	Kilometer square
Km	Kilometer
M^3	Cubic meters
m.a.s.l	meters above sea level
MCMC	Monte Carlo Chain of Marks
MK	Mann-Kendall
MoWIE	Ministry of Water, Irrigation, and Electricity
NSE	Nash-Sutcliffe efficiency
NMA	National Meteorological Agency
NOAA	National Oceanic and Atmospheric Administration
NOx	Nitrogen Oxides
OIDA	Oromia Irrigation Development Authority
PEST	parameter estimation process
ParaSol	Parameter Solution
PBIAS	Percent bias
POS	Particle Swarm Optimization

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QGIS	Q Geographic Information Systems
QM	Quantile mapping
R^2	Determine coefficient
RCMs	Regional climate model
RCPs	Representative Concentration Pathways
SCS	Soil conservation service
SEI	Stockholm Environment Institute
SNNPR	Nations, Nationalities, and Peoples of the South Region
SPSS	Statistical Package Social Sciences
SRES	Emission Scenarios Special Report on Emission Scenarios
SRFD	Special Report on Future Directions
SSPs	Shared Socioeconomic Pathways
SUFI-2	Automatic Sequence Uncertainty Correction
SWAT	Soil and Water Assessment Tool
USDA-ARS	United State Department of Agriculture, Agricultural Research Service
USGCRP	United State Global Change Research Program
W/m^2	Watts per square meter
WBM	Water Balance Model
WCRP	World Climate Research Program
WEAP	Water Evaluation and Planning
95PPU	95% prediction uncertainty

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CHAPTER ONE

INTRODUCTION

1.1 Background

Potential climate change has a significant impact on regional and local hydrological cycles (IPCC, 2007; Solomon *et al.*, 2007; Kundzewicz, 2008; IPCC, 2012; IPCC, 2013, Ma *et al.*, 2020), especially on precipitation and evaporation (Shrestha *et al.*, 2020). Water scarcity in the river basin is a recent problem that has its roots in climate change, which alters the amount and frequency of precipitation (Setegn *et al.*, 2011; Ejder *et al.*, 2016a; Kale *et al.*, 2016a; Gardoni *et al.*, 2016). It also causes drought and flooding, rising sea levels, and prolongs the dry season (Giorgi *et al.*, 2011; Ahmadalipour., 2019; Hosseinzadehtalaei *et al.*, 2020). Potential impacts could raise the probability, regularity, and extreme weather events occurring frequently both locally and globally (Githui *et al.*, 2009; Amadou *et al.*, 2014; Shamir *et al.*, 2015, Arnell *et al.*, 2019). Every aspect of water availability is impacted by climate change, including distribution, resource management, hydroelectric power generation, irrigation, agricultural planning, and irrigation management (Kang and Khan, 2009; Seiller and Anctil F, 2014).

Climate change global and regional consequences will worsen in the next decades as mean temperatures rise (Solomon *et al.*, 2007; Immerzeel *et al.*, 2012; Sorg *et al.*, 2012; Wu *et al.*, 2012; Yang *et al.*, 2012; Sorg *et al.*, 2012; Wu et *al.*, 2012; Seager *et al.*, 2013; Yang *et al.*, 2013; Yang *et al.*, 2014; Li and Fang, 2017; Arnell *et al.*, 2019). The two main driving forces of natural processes and human activity are two elements involved in the processes that lead to the emissions of greenhouse gases and carbon dioxide into the atmosphere, which are what is causing this temperature rise (Hegerl *et al.*, 2007; IPCC, 2007; IPCC, 2013; IPCC, 2014; Shamir *et al.*, 2015; Xi-Liu *et al.*, 2018).

According to the IPCC (2013), global temperatures will continue to rise by 1.4 to 5.8 °C if concrete measures are not taken to lower emissions of greenhouse gases. The entire planet's increased in temperature by 0.3 to 0.6 °C since 1900. Climate change will harm the annual or seasonal streamflows, runoff, and amounts as well as the spatial and temporal distribution of hydrological processes in river basins (Allan, 2011; Johnston, 2012; Solaun et al., 2014; Arent et al., 2014) also considered are the timing and spatial arrangement of hydrological processes in river basins (Kumar *et al.*, 2017). The availability of water could also be significantly impacted (Gosling et al., 2011; Sheffield *et al.*, 2012; Chang and Bonnette, 2016) resulting in reduced water availability for irrigation (Kundzewicz, 2008; IPCC, 2013), hydroelectric power generation (Seiller and Anctil, 2014), rainfed agriculture, other water uses river basin water, and environmental activities over the next decades (Bae *et al.*, 2008; Eslamian *et al.*, 2011; Arnell and Gosling, 2016). According to Holman, (2006), as temperatures rise, a greater overall need for water arises, particularly for irrigation (Wang *et al.*, 2014).

The two primary complementary responses mitigation and adaptation options are intended to lessen and manage the effects of climate change. Options for mitigation can assist in reducing global warming and extreme weather events will occur less frequently if greenhouse gas emissions are reduced and climate change emissions are while increasing carbon sinks (Lu, 2013; IPCC, 2001). Adjusting the systems or expected climatic stimuli and implementing them in response to an actual or projected climate stimulus are referred to as adaptation options (IPCC, 2001; Pan and Zheng, 2010; IPCC, 2014). Accordingly, adaptation is the process of changing something to suit

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a purpose and changing natural or human systems to increase the resilience or decrease the vulnerability of a response to climate change effects that have been seen or are expected. Mitigation strategies demonstrate responsible behavior on a global level, whereas adaptation strategies demonstrate responsible behavior on a local level.

Precipitation, temperature, and river streamflow patterns have all changed significantly because of the effects of climate change worldwide. Evaluation of these hydrological and meteorological variables' trends test change analysis has attracted a lot of attention because it can be used to forecast change and manage water resources for a variety of industries and uses (Ahmad et al., 2015). It is important to understand whether or not these hydroclimatic variables are statistically significant in order to evaluate temperature, precipitation, and streamflow data over the long term and short term. Recognizing the trends that the anticipated effects of climate change have activated is essential. Research on water availability and streamflow in the river basin is also essential. Planning and managing water resources, encouraging long-term economic expansion, and predicting outcomes and behavior of climate change all require knowing how precipitation is distributed both spatially and temporally, streamflow and temperature, and trends at the scale of the river basin.

Climate change models from the coupled model intercomparison project 5 (CMIP5) are the most widely used tools for climate change impact analyses for predicting the future and plausible greenhouse gas (GHG) emissions under various four Representative Concentration Pathways (RCPs) (RCP2.6, RCP4.5, RCP6.0, and RCP8.5) (IPCC, 2014). Process improvements between the Coupled Model Intercomparison Project Phase 5 (CMIP5) models and the CMIP3 archive (Meehl et al., 2007). For upcoming projections of climate change and analyses of its effects,

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CMIP5 multi-model ensembles from Phase 5 have been developed (Tayler et al., 2012). The IPCC's Fifth Assessment Report notes that (2013), these models capture the physical, chemical, biological, and mathematical processes and reactions that occur in the atmosphere, on land, in the ocean, and in the cryosphere. They also capture the interactions between the climate system and its components and also forecast future climate variables (predictors), such as precipitation and temperature, as well as results of climate change (Ramirez *et al.,* 2013; Su *et al.,* 2013; Perez *et al.,* 2014; IPCC, 2014; Gulizia and Camilloni, 2015; Nair *et al.,* 2015).

Impact studies on climate change and evaluations of climate change's effects, hydrological models can be used to simulate and transfer the hydrological conditions. Using information from the GCMs and RCMs models, hydrological models can simulate hydrological conditions. At the regional and river basin levels, the models are intended to calculate the future impact of climate change on hydrological cycles, processes, and streamflow. research into the effects of climate change is conducted all over the world using hydrological models, such as the Soil and Water Assessment Tool (SWAT), HEC-HMS, Water Evaluation and Planning (WEAP), Hydrologic Simulation Program-FORTRAN (HSPF), and Water Balance Model (WBM), among others. These various hydrological models allow us to forecast, visualize, and recognize how the river basin area's streamflow and water availability will be impacted by climate change (Evans and Schreider, 2002; Christensen *et al.,* 2004; Bae *et al.,* 2008; Fujihara *et al.,* 2008, Han *et al.,* 2018. Dang *et al.,* 2020).

1.2 Problem Statement and Justification

Rivers are regarded as the lifeblood of Ethiopia because they supply water for domestic use, hydroelectric power production, and irrigation. They also produce the majority of the hydropower

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and agricultural output. The Omo-Gibe River basin is the biggest and most significant of the 12 river basins in the nation. In addition, after the Blue Nile, it is the second-largest river system in Ethiopia. Three (3) cascade dams, Gibe III Gibe II, and Gibe I Gilgal are located in the basin and together produce 45% of Ethiopia's hydroelectric power.

Climate change impact has resulted in water shortages for the generation of hydropower and other purposes in the basin of the Omo-Gibe River over the last decade. The government of Ethiopia declared in May 2019 that climate change had generated a 476-megawatt electricity deficit in the Omo-Gibe River Basin's Gibe III dam which accounts for approximately one-third of Ethiopia's electricity generation of 1,400 Megawatts.

Cascade dams in the Omo-Gibe River basin also provide water for the irrigation of 67,928 hectares of valuable agricultural land. Currently, various water resource developments are underway, including the development of a sugar plantation and the construction of sugar factories in the lower Omo-Gibe valley. Gibe IV, another cascade dam, is also under construction, and Gibe V is in the design stages for hydropower generation.

Thus, in the Omo-Gibe River basin, precipitation levels, frequency, seasonal distribution, and magnitude must be accurately predicted and quantified in order to understand how future climate change will impact these factors. Droughts are common in this river basin and have already caused major losses in various productive sectors (Degefu and Bewket, 2014). Developing adaptation strategies is essential, to reduce the result of climate change, sustainability in water use and management, and safeguard against floods and droughts since in the basin of Omo-Gibe-River basin no major research has been conducted on the impact of climate change on the future availability of water for irrigation and hydropower generation. This research will close a

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knowledge gap and provide data on anticipated climate change impacts, streamflow, and water availability for irrigation and hydropower generation in the future

1.3 Objectives of the Study

The main objective of this study was to quantify and predict the impact of climate change on the future availability of water for irrigation and hydroelectricity generation under two RCP4.5 and RCP8.5 climate change emission scenarios in the Omo-Gibe basin.

The specific objectives were to:

1. Project the impact of climate change on future precipitation amounts, seasonal distribution, and streamflow.

2. Quantify and project the impact of climate change on the future availability of water for irrigation and hydropower generation.

3. Identify climate change adaptation options for the future availability of water for irrigation and hydropower generation.

1.4 Research Questions

1. How will climate change affect the future amount of precipitation, seasonal distribution, and streamflow in the Omo-Gibe River Basin?

2. How will climate change impact the amount of water available for irrigation and hydropower generation?

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3. Which climate change adaptation strategies in the Omo-Gibe River basin will significantly reduce the impacts of climate change on the availability of water for irrigation and hydropower production in the future?

1.5 Scope of the Research

The scope of the study is to project and quantify the amount of water that will be available for irrigation and hydropower generation and how climate change will affect future water availability in the future. Climate change projections using a fifteen-model multi-model ensemble average RCMs, under two (2) climate change scenarios RCP4.5 and RCP8.5. The projections for climate change covered three (3) periods: the near future (2017-2044), the medium future (2045-2072), and the far future (2073-2100). Hydrological conditions: future streamflow, water availability, allocation, and demand estimation and prediction for irrigation and hydropower generation using coupled SWAT and WEAP hydrological models.

1.6 Limitations of the Study

Due to the lack of data on the groundwater in each sub-basin, the appropriate strategy could not be investigated as it required more time and resources.

1.7. Structure of the Thesis

The thesis is divided into five (5) Chapters. Chapter One is the introduction of the study, points out the reasons for the study, and explains why it is being done. Chapter Two presents background and literature on global warming, assessment reports of the intergovernmental panel on climate change and climate change scenarios, weather prediction models, general circulation models, and climate change projections, coupled model intercomparison project, regional climate model, and

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downscaling climate data, bias correction of climate data, impacts of climate change on water resource, impacts of climate change on precipitation and streamflow, impacts of climate change on water availability for hydropower generation, climate change's effects on water availability for irrigation, hydrology, hydrological modeling, hydrological models, classification of hydrological models, past studies on the impacts of climate change in the Omo-Gibe River, global adaptation options to climate change and coping with the impacts of climate change and the present study are unique from previous research are presented in this Chapter. Chapter Three outlines the study areas and gives information on the materials and methods used to arrive at the study's conclusions. Chapter Four presents the result and discussion of the findings of each of the three particular objectives. Chapter Five presents a summary of the key study findings; draws useful conclusions from the study and also provided recommendations for policy and further studies of the study flow chart shown in (Figure 1.1).

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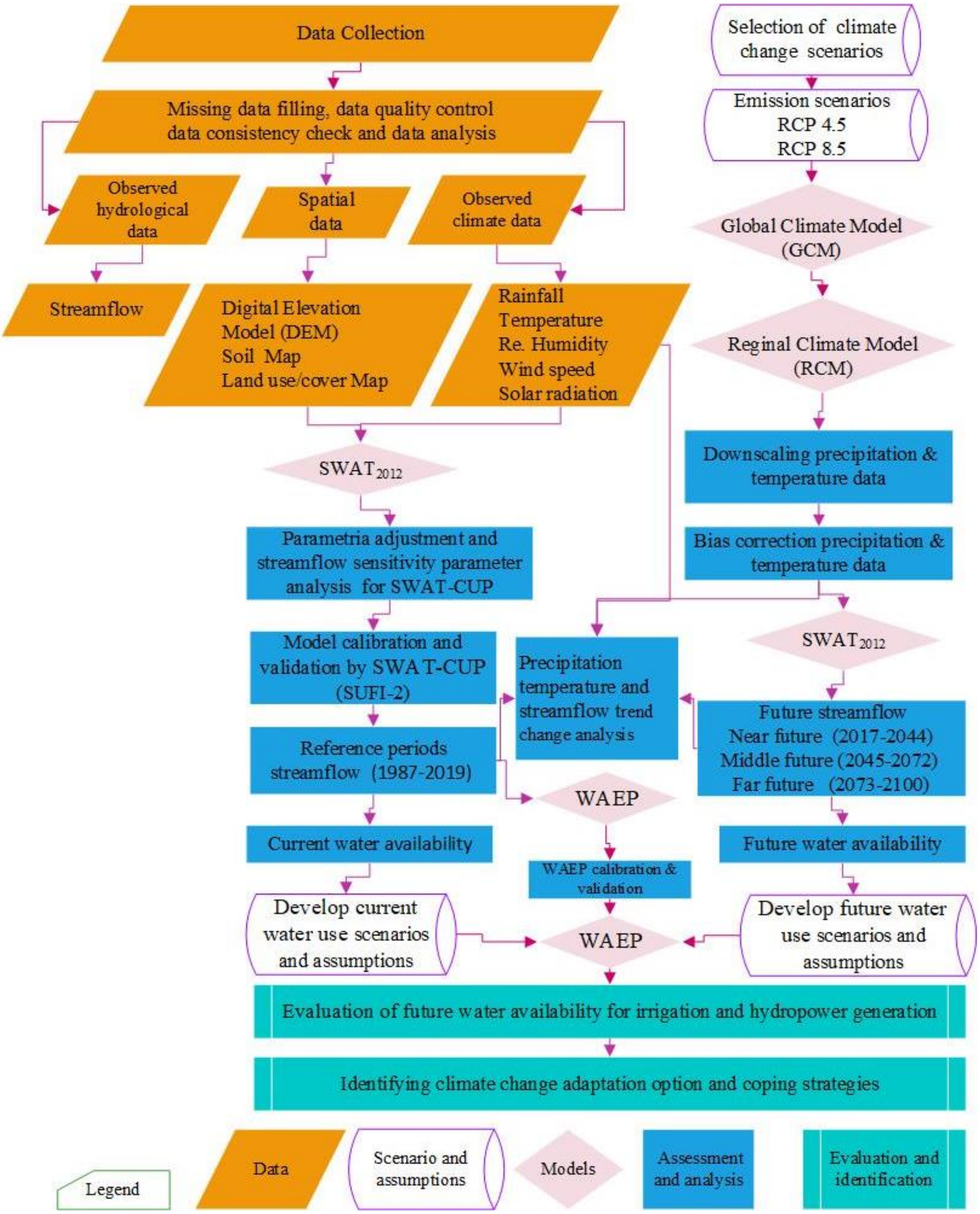

Figure 1.1: Conceptual Framework. (Author's Construct, 2022).

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CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

In this Chapter, the impacts of climate change on future water availability for irrigation and hydropower generation were examined. This Chapter compiled detailed information from research evaluations and earlier studies in order to create a framework for carrying out this research study more successfully and effectively.

2.2 Global Warming and Climate Change

The terms "global warming" and "climate change" are frequently used interchangeably even though they refer to different phenomena. When we talk about "global warming," we're talking about an increase in greenhouse gas concentrations in the atmosphere that increases the planet's average surface temperature. According to (Whitmarsh and O'Neill (2010); Budzianowski (2011); Chophel (2021); and Johnsson *et al.*(2019), the gases that are released into the atmosphere are to blame for the phenomenon of global warming. Human activities, such as the production of electricity from the burning of fossil fuel, industrial processes, land use change such as urbanization and deforestation, land use and land use change, energy production, and specific agricultural practices contribute to the production of these gases (Edenhofer *et al.*, 2014), while natural processes such as earthquakes, mud volcanoes, and volcanic activity, forests, fires, oceans, permafrost, and wetlands (Yue and Gao, 2018). These greenhouse gases act as a shield around the planet, absorbing solar energy and raising atmospheric concentrations of these gases, which warms the atmosphere and increases the average global temperature. Global warming is one of the primary factors contributing to climate change is greenhouse gas emissions, which have an impact on the planet's average surface temperature. Greenhouse gases are to blame for the increase in temperature. On the other hand, global warming describes a persistent rise in the world's average temperature.

When we talk about "climate change," we mean the shift in weather patterns that are primarily brought on by greenhouse gas emissions. This phrase describes the temperature changes that have a long history, humidity, precipitation, patterns of wind, clouds, and barometric pressure of the atmosphere. However, the more precise term for these climate change refers to long-term changes in the planet's weather patterns. (IPCC, 2018). Whenever "weather" is mentioned, it refers to the climatic conditions at any given moment, hour, day, or season. It alludes to typical circumstances that have existed for at least 30 years. According to Solomon *et al.* (2007), climate change has the power to change statistical traits, global climate system status, and global or regional climate trends. Its capability can the local averages for the wind, temperature, humidity, barometric pressure, and precipitation should be changed. Climate change may have an immediate and long-term impact on the quantity and frequency of precipitation as well as its seasonal distribution, streamflow, and availability of water (Trenberth *et al.,* 2007; IPCC 2013; Ejder *et al.*, 2016a; Kale *et al.,* 2016a; Arnell and Gosling, 2016)

One of the main contributors to climate change is the rise in the atmospheric concentration of greenhouse gases. According to the National Academy of Sciences (2020), carbon dioxide, methane, and nitrous oxide are the three primaries naturally occurring greenhouse gases. Fluorinated gases also contribute to global warming, including hydrofluorocarbons, perfluorocarbons, sulfur hexafluoride, and nitrogen trifluorides. These naturally occurring gases

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can trap heat in the atmosphere and cause warming, which in turn contributes to global warming; since the Industrial Revolution, human activity has resulted in higher concentrations of the main greenhouse gases... The earth would be too chilly for life to exist if the greenhouse effect is absent. Because more greenhouse gases are being trapped in the earth's atmosphere, global temperatures have been rising over time. Socio-economic factors, human activities, and natural processes all have an impact on greenhouse gas emissions, which in turn have an impact on atmospheric and climatic processes (Figure 2.1).

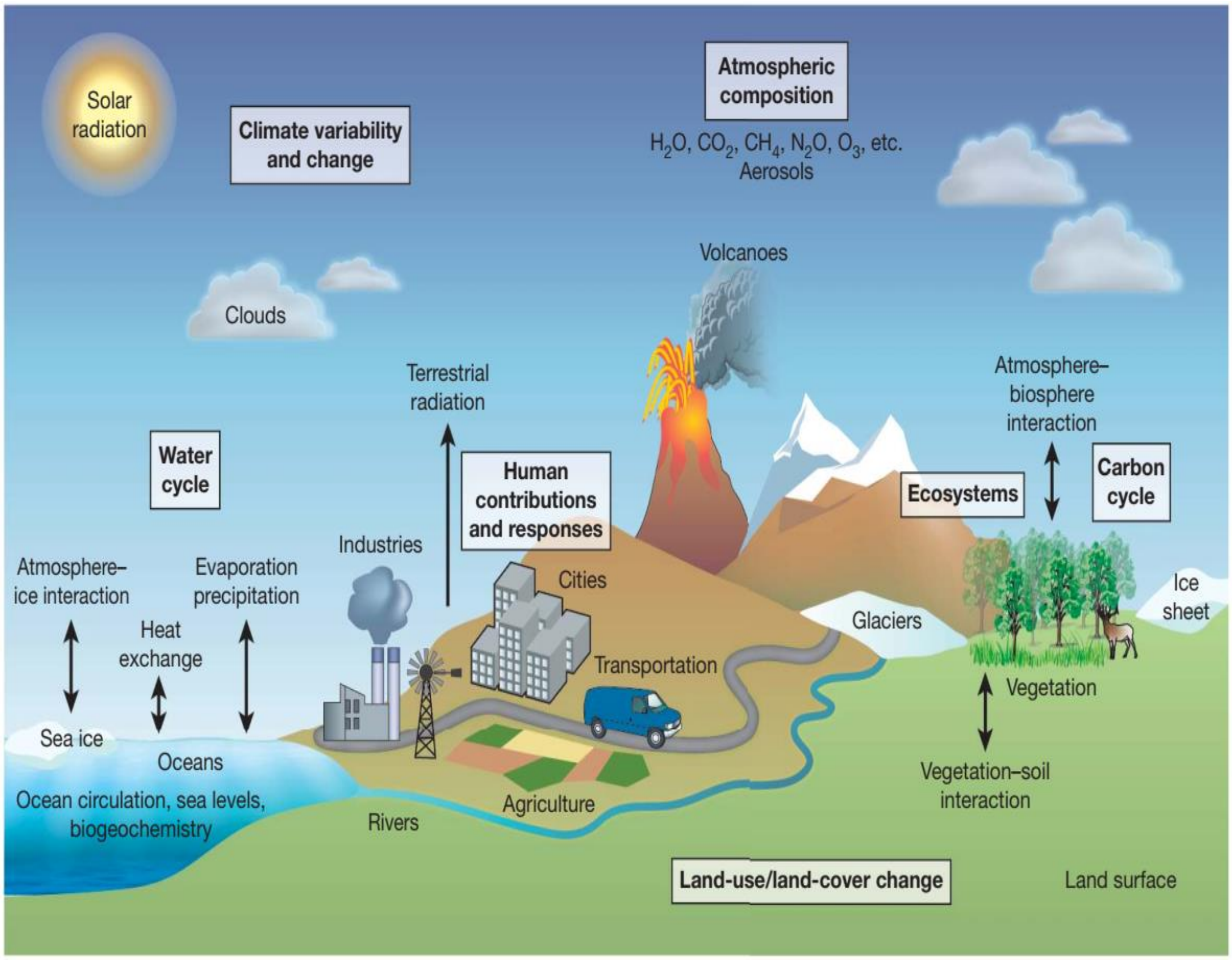

Figure 2.1: Primary Natural and Human-Made Processes and Effects on the Climate System. (Adopted from Baede *et al.*, 2001)

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2.3 Intergovernmental Panel on Climate Change (IPCC) Assessment Reports and Climate Change Scenarios

Assessment reports offer scientific data that can be used by governments around the world to make decisions about how to address climate change. For global climate negotiations, these reports are helpful. A climate scenario, on the other hand, is a collection of climatological relationships and radiative forcing assumptions that offer plausible accounts of how the future might develop in many important areas, such as greenhouse gas emissions, socio-economic, technological, and environmental conditions, and aerosols. These scenarios represent future climatic conditions, despite being frequently oversimplified. Models that simulate the effects of climate change frequently have inputs created specifically for them. The future's possible outcomes can be predicted using climate change scenarios. What could happen, and even "What should happen?". Additionally, it is an effective tool for determining climate change, creating adaptation plans, and influencing climate policy. Climate change scenarios also referred to as socioeconomic scenarios, are used by analysts to forecast future greenhouse gas (GHG) emissions and determine how vulnerable the world is to them. Variations in temperature, population, emissions of greenhouse gases (GHG), and time evolution are all included in the scenarios.

IPCC First Assessment Report (AR1) developed four emission scenarios in 1990 as the so-called SA90 scenarios (Houghton *et al.*, 1990). The IS92 set of IPCC scenarios, also known as the second set, was released in 1992 (Leggett *et al.*, 1992). Long-term emission scenarios were developed by the IPCC (Pepper *et al.*, 1992). Numerous studies have been conducted regarding potential climate change, its effects, and possible mitigation strategies using these scenarios, which center on developing a climate change inventory. In 1995, the 1995 IPCC scenarios were assessed, and the

IS92 emissions scenarios were used in climate simulation models to quantitatively assess their effects. There were two different economic growth paths and the same demographic projections across all emission scenarios. Two (2) of the scenario variants were used as references, and the other two (2) were mitigation techniques that shared the majority of the other underlying assumptions with the reference scenarios

The IPCC's Second Assessment Report (AR2) and the first Special Report on Future Directions (SRFD) (Alcamo *et al.*, 1994) were both released in 1995. The study suggested taking into account significant advancements in emissions drivers and techniques since 1992. This new understanding has an impact on sulfur emissions, the income gap between developed and developing nations, and the CO_2 intensity of the energy supply, among other things. Six (6) reference emission scenarios from IS92 are among the most shocking scenarios ever created. They were based on three (3) different population projections that took into account a range of potential demographic outcomes, five (5) potential directions for economic growth, and, perhaps most significantly, a range of potential downstream emissions. The four (4) other radioactive gases, including sulfur dioxide and NOx, as well as the six "Kyoto" greenhouse gases, were among the first to be incorporated into the IS92 scenarios. The primary scenario of the Six, IS92a, is still referenced and replicated in the current literature, and some considerations are also found in more recent work.

The Special Report on Emission Scenarios (SRES) was produced by the IPCC Plenary, and it in 1996, contained several emission scenarios. The IPCC Third Assessment Report (AR3), which focused on stabilization scenarios, was released in 2000, four (4) years after the so-called SRES was released (Nakicenovic, 1996). The Fourth Assessment Report (AR4) of the IPCC was released seven (7) years later (IPPC, 2007). Six (6) emission scenarios were released in the Special Report

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on Emissions Scenarios (SRES). A1FI, A1B, A1T, A2, B1, and B2 are the designations for SRES scenarios. A1T and B1, which are creating clean energy technologies, present the most promising opportunities. Climate change simulations using scenarios A1FI and A2 showed a significant increase in CO_2 emissions (Reference).

Social and economic factors, human activities, and natural processes all have an impact on greenhouse gas emissions, which in turn have an impact on atmospheric and climatic processes. In Figure 2.2, At the end of the twenty-first century, projected CO2 emissions for the SRES emission scenarios are displayed.

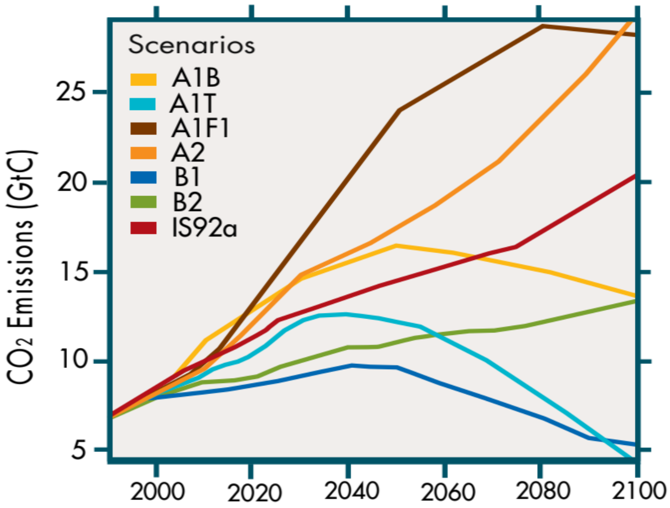

Figure 2.2: Projected Future Carbon Emissions for the SRES Emission Scenarios. (Adopted from Third Assessment Report of IPCC Working Group I, 2007).

Copenhagen, Denmark, hosted the 2014 IPCC and released its Fifth Assessment Report. Report five of the IPCC's assessment recommended using four (4) scenarios to forecast future climate change. These are referred to as RCPs (Representative Concentration Pathways) scenarios. Those four (4) options that differ from one another have been developed: RCP6.0, RCP8.5, RCP4.5, and RCP2.6 four research projects to enforce emission levels for 2100 (IPCC, 2013). The scenarios

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are employed to research and project how future land use, energy consumption, population growth, socioeconomic development, and technological advancement will be impacted by global warming. The projections demonstrate how various greenhouse gas emissions will impact global warming by 2100.

RCP2.6, the mitigation scenario with the most favorable outcomes, shows the lowest carbon dioxide levels, according to (van Vuuren et al. 2011). By 2050, It will arrive at its mid-century peak of around 3.1 W/m^2, and by 2100, it will have dropped to 2.6 W/m^2 (van Vuuren *et al.*, 2007a). RCP 6.0 and RCP 4.5 are two potentials, stabilizing options for the middle term. According to Thomson *et al.* (2011), the long-term force of the radiation target level is not exceeded in the scenario for stabilization known as RCP 4.5, where radiative forcing stabilizes at 4.5 W/m^2 shortly after 2100. According to Wise *et al.* (2009), it stabilizes around the year 2100 without going above the target level for long-term radiative forcing. According to Masui *et al.* (2011), RCP 6.0 is a scenario for stabilization that uses different technologies and tactics to reduce carbon dioxide emissions. In this scenario, the total radiative forcing of 6.0 W/m^2 stabilizes not long after 2100, overshooting. The bleakest possible scenario for emissions, RCP 8.5, which increases emissions as business as usual, is accompanied over time by rising greenhouse gas emissions. The maximum value of the radiative force is 8.5 W/m^2, as reported by Rajsekhar and Gorelick (2017) and Riahi *et al.* (2011), which results in a significant concentration of greenhouse gases. These climate scenarios presented by Moss *et al.* (2010) and Tayler *et al.* (2012) depict a collection of illustrative concentration curves, climate zones, and workable future scenarios according to various land use assumptions, usage of energy, population expansion, socioeconomic development, and technological advancement. These hypotheses lead to the RCP emission scenarios for the 21st century, which are depicted in (Figure 2.3).

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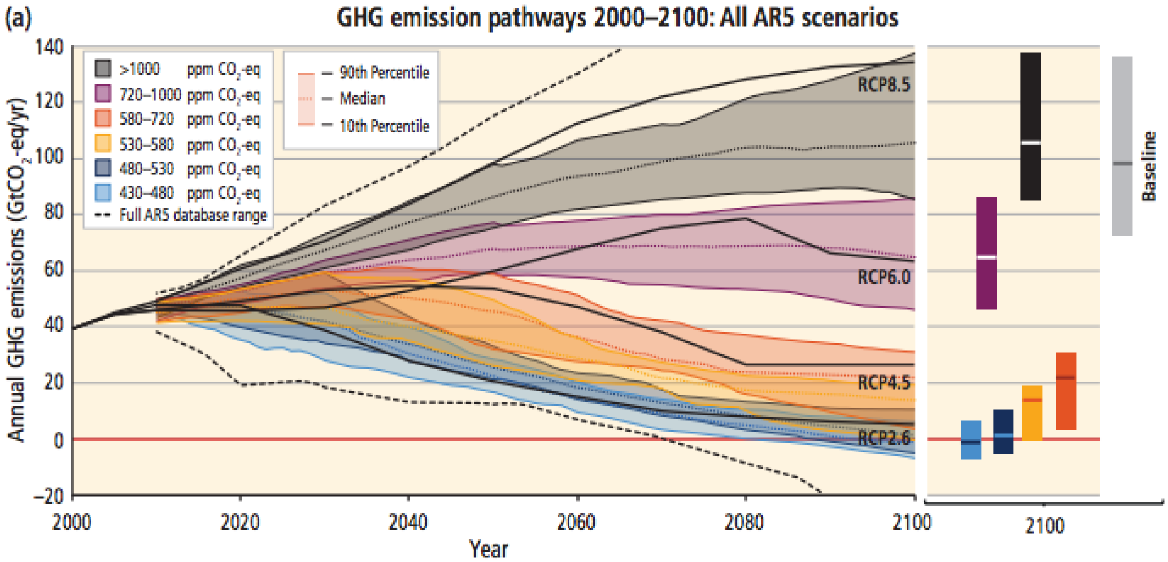

Figure 2.3: Projected Future Carbon Emissions for the RCP Emission Scenarios Over the 21st Century. (Adopted from Fifth Assessment Report of IPCC Working Group I, 2013).

According to the Sixth Assessment Report of the IPCC, which was published in April 2022, the sixth assessment cycle of the international body assessing climate change is now finished. This organization was created specifically to offer policymakers recurring assessments of the science underlying climate change. The IPCC Sixth Assessment Report (AR6) suggested five (5) approaches for analyzing and projecting various emission scenarios related to climate change. The five (5) anticipated emission scenarios are represented by a fresh set of socioeconomic hypotheticals called Shared Socioeconomic Pathways (SSPs), which are SSP1-1.9 (extremely low), SSP1-2.6 (low), SSP2-4.5 (moderate), SSP3-7.0 (high), and SSP5-8.5 (very high) (Collins *et al.*, 2017; Lurton *et al.*, 2018).

The IPCC AR6's product scenarios cover a wide range of potential futures for greenhouse gas emissions, from one in which carbon emissions are drastically reduced by 2050 and become carbon neutral and negative in the 20th century's second half (SSP1-1.9) to another in which they rise

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sharply to double current levels in 2050 and more than triple current levels in 2100 (SSP5-8.5). Five distinct future CO_2 emission scenarios are presented in (Figure 2.4) and are based on conceivable social developments in the twenty-first century.

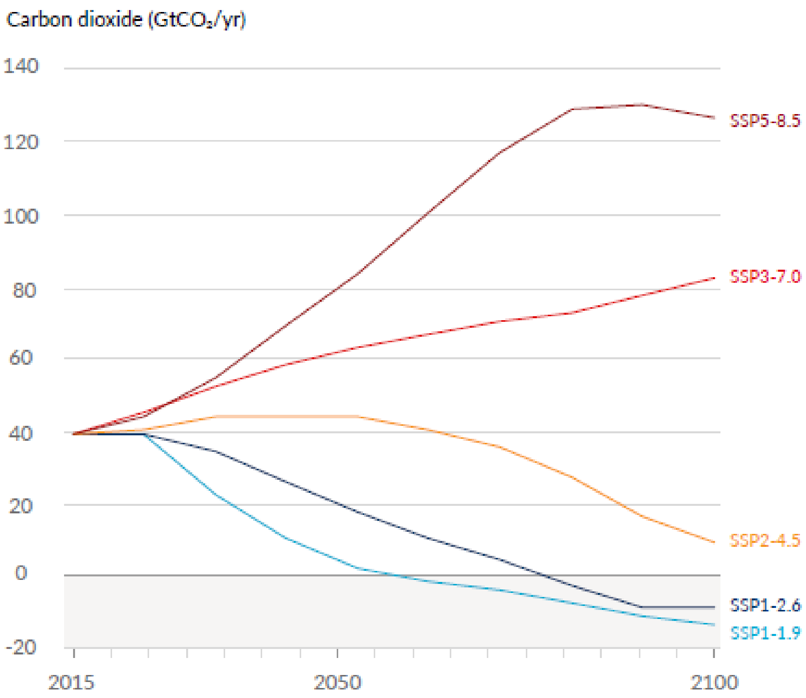

Figure 2.4: Future CO2 Emissions Have Been Constructed from Plausible Developments in Societies Over the 21st Century. (Adopted from Sixth Assessment Report of IPCC Working Group I, 2021).

2.4 Weather Prediction Models

Weather models should only be used for limited geographic areas and short-term (up to two weeks) forecasting horizons. Meteorologists can forecast both present and future atmospheric conditions using weather data and forecast models. To forecast the weather, hourly weather data are combined with forecast models that consider the atmosphere and the ocean's current state. When making a forecast, factors such as precipitation, humidity, temperature, barometric pressure, wind direction, and speed, cloud cover, and others are all taken into consideration.

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Climate models, a broader category of the weather forecast, look over long periods to forecast how an area's typical weather patterns will change over the next few decades. Models make it possible to simulate interactions between the land surface, atmospheres, oceans, and ice quantitatively. These are mathematical simulations of the climate system that depict a variety of significant aspects of the average climate, including the distribution of atmospheric precipitation, temperature, radiation, and the presence of sea ice, strong winds, and sea temperatures.

2.5 General Circulation Models (GCMs) and Climate Change Projections

A general circulation model (GCM), also called a Global climate model (GCM), and is a numerical simulation of Earth's natural systems that simulates important components of the climate system. (Solomon *et al.,* 2007; Alley *et al.,* 2007). Models are essential tools for correctly forecasting climate change brought on by increasing greenhouse gas emissions concentrations and simulating responses to their emissions (IPCC, 2007). These models offer fundamental insights into fluid dynamics and thermodynamics and forecast the climate for the next century and beyond while simulating potential future climate zones.

GCMs are the most reliable methods for forecasting and representing atmospheric and oceanic circulation in physical characteristics of gases and liquids described by equations. These large-scale models are currently being used to simulate large-scale atmospheric circulation patterns all over the world, advancing scientific understanding of the large-scale variability and change in climate variables (Dixon *et al.,* 2016). The models provide information about the climate in the future by predicting global and regional climate change, assessing risks, determining appropriate policies to address the issue, and developing adaptation plans (IPCC, 2014). Three-dimensional numerical climate change models are used by scientists to forecast regional and global climate

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conditions (Gulizia and Camilloni, 2015; Nair *et al.*, 2015; Perez *et al.*, 2014; Ramirez *et al.*, 2013; Su *et al.*, 2013). These simulations depict the physical processes and reactions that occur in the cryosphere, on land, in the ocean, and in the atmosphere.

Future climate change can be predicted using a number of multi-model ensembles produced by the Coupled Model Intercomparison Project Phase 5 (CMIP5) (Tayler et al., 2012). The CMIP5 has produced a variety of multiple-model ensembles that is a method for predicting upcoming climate changes (Tayler et al., 2012). Input based on the AR5, the Fifth Assessment Report of the IPCC was used to build the model, which projects past, present, and future climate changes, rising greenhouse gas concentrations, evaluation of climate change's local and global effects using climate projections and climate variables (IPCC, 2013; IPCC, 2014). Climate variables and changes to project (Moss RH *et al.*, 2010; van Vuuren *et al.*, 2011), Four (4) climate scenarios known as Representative Concentration Pathways (RCP) are used by these models: RCP8.5, RCP6, RCP4.5, and RCP2.6 (Thomson *et al.*, 2011; Masui *et al.*, 2011). Several external factors that are significant inputs to the models determine how much solar energy is absorbed by the earth or captured by the atmosphere. There are many grid cells, and each one represents a section of the earth's surface that is oriented both vertically and horizontally. The idea behind climate models calculates the required inputs depicted in (Figure 2.5)

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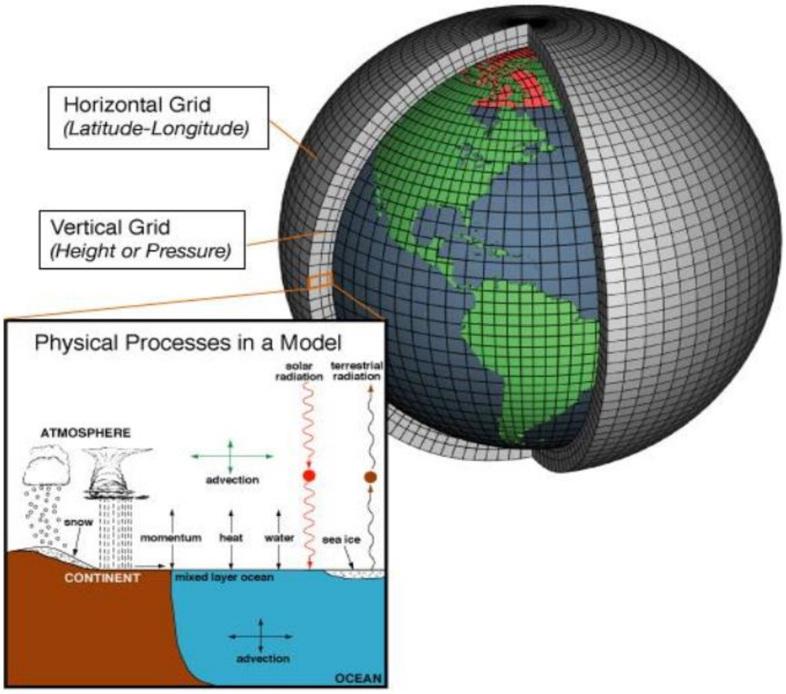

Figure 2.5: The Concept Used in Climate Models Calculate Winds, Heat Transfer, Radiation, Relative Humidity, and Surface Hydrology Within Each Grid and Evaluate Interactions with Neighboring Points. (Adopted from National Oceanic and Atmospheric Administration-NOAA, 2012).

In-depth climate simulations cannot be produced by GCM models at the local and regional scales because of their lack of resolution. Downscaling is a great way to address this issue as it results in higher spatial resolution than the GCMs. The limitations of low-resolution climate data make it difficult for GCMs to assess the effectiveness of local and regional climate change forcings, such as complex topography and land surface features, to accurately represent. Regional data are enhanced or improved by downscaling methods using regional climate models. GCM to RCM data projection approach for regional climate models and an analysis of climate change's effects are shown in (Figure 2.6).

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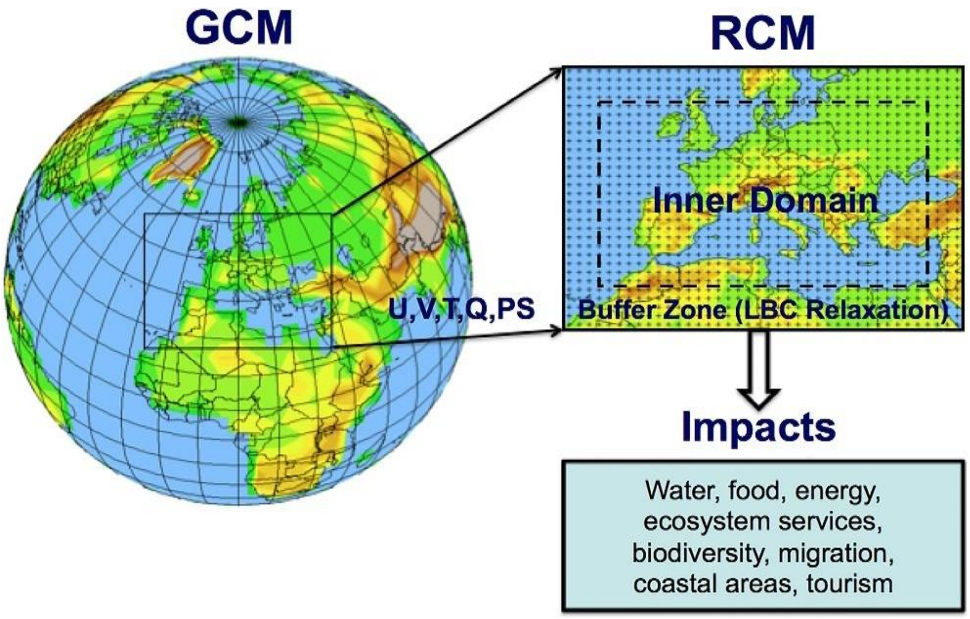

Figure 2.6: GCM to RCM Data Projection Approach and Climate Change Impact Assessment. (Adopted from Thirty Years of Regional Climate Modeling: Where Are We and Where Are We Going Next? 2019).

2.5.1 Coupled Model Intercomparison Project (CMIP)

Many GCMs models have been developed and are available for analyzing and forecasting climate change's consequences. Consider the CMIP3 document (Meehl *et al.*, 2007) derived from Coupled Model Intercomparison Project Phase 3. It is used in the Fourth Assessment Report on Climate Change by the Intergovernmental Panel on Climate Change (IPCC, 2007), which also includes 25GCM's findings. The Fifth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2013) contains findings from 61 different GCMs and is referred to as the CMIP5 document (Tayler *et al.*, 2012). In its sixth phase, Coupled Model Intercomparison Project 6 (CMIP6), more than 40 GCMs produced by various modeling firms are included (Tebaldi *et al.*, 2021).

CMIP's main objective is to offer a multi-model context for a better understanding of climate change's past, present, and future. A popular technique for determining studies on the effects of climate change globally and its effects is the using a GCM application with multiple models. Utilizing the results of the CMIP is now considered the best practice for the evaluation of climate change's effects. These multi-GCM ensembles of global climate GCM models allow GCM errors to cancel out and incorrect GCMs to add data, increasing accuracy and reducing uncertainty in long-term climate change projections (Pierce *et al.*, 2009).

2.5.2 Regional Climate Model and Downscaling Climate Data

The World Climate Research Program (WCRP) currently deployed the programme Coordinated Regional Climate Downscaling Experiment (CORDEX) RCM to develop regional climate predictions from high-resolution data for all worldwide regions (*Giorgi et al., 2009*) driven by the CMIP5 model. These regional Models have been created and are being used to provide comprehensive climate data because of their ability to resolve smaller atmospheric phenomena entangled with large-scale climate forcing (Prudhomme *et al.*, 2012; Mezghani *et al.*, 2017). The climate variables are represented with spatial and temporal resolution and at the regional level projections and evaluations of the future state of the climate based on GCM results are insufficient. But the output of the fine-scale RCM model is more accurate than that of the GCM when used as a direct input for hydrological models and for calculating the regional impact of climate change (Elsner *et al.*, 2010).

Climate variables from GCM models are not sufficiently represented in space, time, or regions. Two (2) fundamental downscaling methods are frequently employed to address this issue: statistics (Anandhi *et al.*, 2008) and dynamics (Domnguez *et al.*, 2012). Approaches are extensively established and frequently utilized for investigating regional climate conditions. Its foundation is the creation of statistical links or linear functions between small-scale fields, like GCM model

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outputs, and local data, under the underlying presumption that historical climate statistics will hold for future climates.

Acharya *et al.* (2013), Sachindra *et al.* (2014), and Sachindra *et al.* (2014) assert that statistical downscaling is based on relationships between large-scale climate information's (predictors') statistical characteristics and regional climate (predictor), using GCM data as a reference (Wilby *et al.*, 2004). These statistical models were also employed to produce future climate data from the output of future GCMs. The mathematical functions used in downscaling, which are based on empirical information from long-term climate time series, validate the statistical relationship. Wilby and Wigley (1997) and Wilby *et al.* (2004) claim that it is employed to produce regional climate variables that largely won't change in the future.

The dynamic downscaling technique, which is constructed with complex local processes and physical realism, extracts local climate using regional nested numerical simulations of physical processes using higher spatial resolution at a finer scale, creating stable conditions and providing more information at a small scale (Abatzoglou and Marrone, 2012; Elguindi and Grundstein, 2013; Burger *et al.*, 2015; Walton *et al.*, 2015). Scientists prefer dynamic downscaling because it can incorporate more systematic properties like topography, dynamic climate processes, etc. while users favor statistical downscaling because of its low computational requirements and quick calculations. In many countries, the results of statistical and dynamic downscaling have been widely disseminated in the fields of hydrology, agriculture, natural disasters, and climate change (*Guo et al.*, 2018; Huang *et al.*, 2018; Zhai *et al.*, 2019). Details of downscaling steps from GCMs to RCMs and River Basin are presented in (Figure 2.7).

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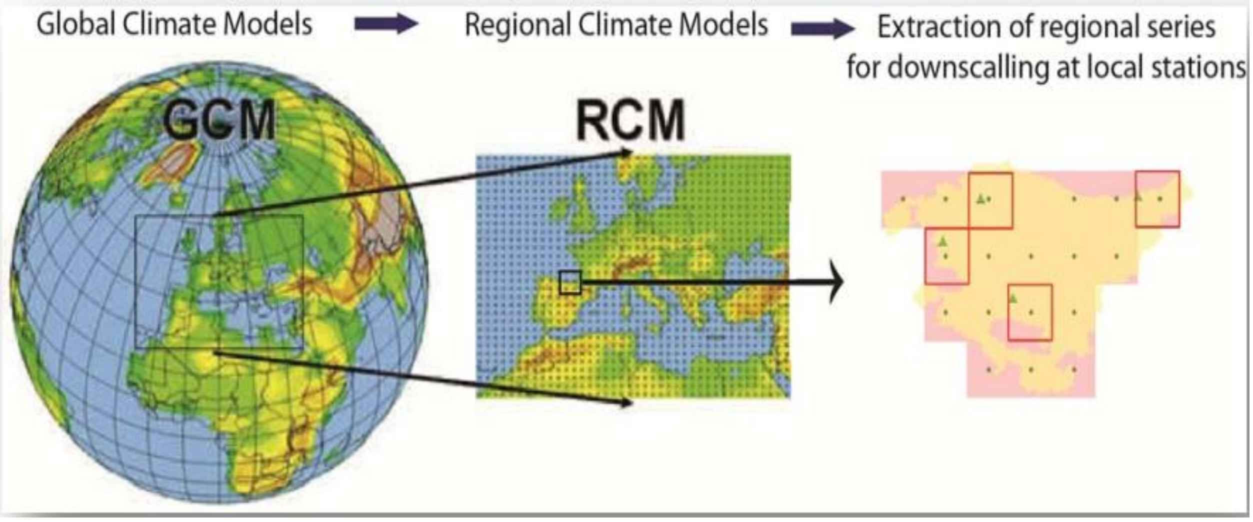

Figure 2. 7 Downscaling from GCMs to RCMs and River Basin. (Adopted from Universidad del País Vasco, 2012).

2.5.3 Bias Correction of Climate Data

The RCM data show a statistical discrepancy between them and the measured climate variables. To correct these distortions, many different techniques have been developed. Processing methods are used to statistically adjust the findings to make the data more relevant and acceptable to customers. Teutschbein and Seibert (2012) provided excellent insight into numerous bias reduction techniques. The recovered correction factors and appendices are considered stationary over time and space by all commonly used methods. It is therefore presumed that they are correct for baseline and scenario periods.

Hawkins *et al.* (2013) and Gebruchorkos *et al.* (2019) report that the output data from GCMs frequently show large anomalies that call for correlation to observe data anomaly correction to improve data reliability and quality and serve as a channel for connecting GCM results to a hydrological model. It is frequently necessary to run climate simulations to correct for bias before using climate data to determine how climate change is affecting the world (Christensen *et al.*,

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2008). Statistical inconsistencies between RCM data and recorded meteorological variables are common, resulting in bias. Sennikovs (2009); Teutschbein and Seibert (2010) and Teutschbein and Seibert (2012) have provided more literature in the area of bias correction.

2.6 Impacts of Climate Change on Water Resources

The principal impacts of climate change are elevated mean surface temperatures, locally decreased precipitation, and decreased water quantity and quality (Flato *et al.*, 2014; Trenberth *et al.*, 2015). According to Bates *et al.*, (2008), Zhang *et al.*, (2008), Elmahdi *et al.*, (2009), and Wang *et al.*, (2013), there is the possibility to change in the amount and frequency of precipitation, as well as its distribution and seasonal variability. Additionally, the availability of water is significantly impacted by climate change through a modification of the water cycle (Chang and Bonnette 2016; Ma *et al.*, 2020). The water resources that are available to meet the needs of all societies, ecosystems, and other water users are impacted by this broad aspect of water availability. This is the general side of water availability; it affects the number of water resources available to meet the needs of all societies, ecosystems, and other water uses. As a result of higher temperatures and increased evapotranspiration, water demand is also impacted by climate change, which can worsen the already existing water shortage.

The regional and global water cycles, as well as the frequency and volume of precipitation, may all be impacted by climate change (IPCC, 2012; IPCC, 2013). Additionally, it can lengthen the dry season, which can result in droughts, rising sea levels, frequent flooding, stress, and a lack of water (Giorgie *et al.*, 2011), as well as modify key hydrological conditions and processes' spatial and temporal distribution (Kumar *et al.*, 2017). Georgi *et al.* (2011) state that, streamflow, water availability, soil moisture, and evaporation levels, as well as the volume and yearly and seasonally

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distributed precipitation, will all be impacted by climate change. Water resources are essential for both people and ecosystems, but climate change may change their quantity and quality. Figure 2.8 depicts the anticipated climate change that has caused changes in water resources.

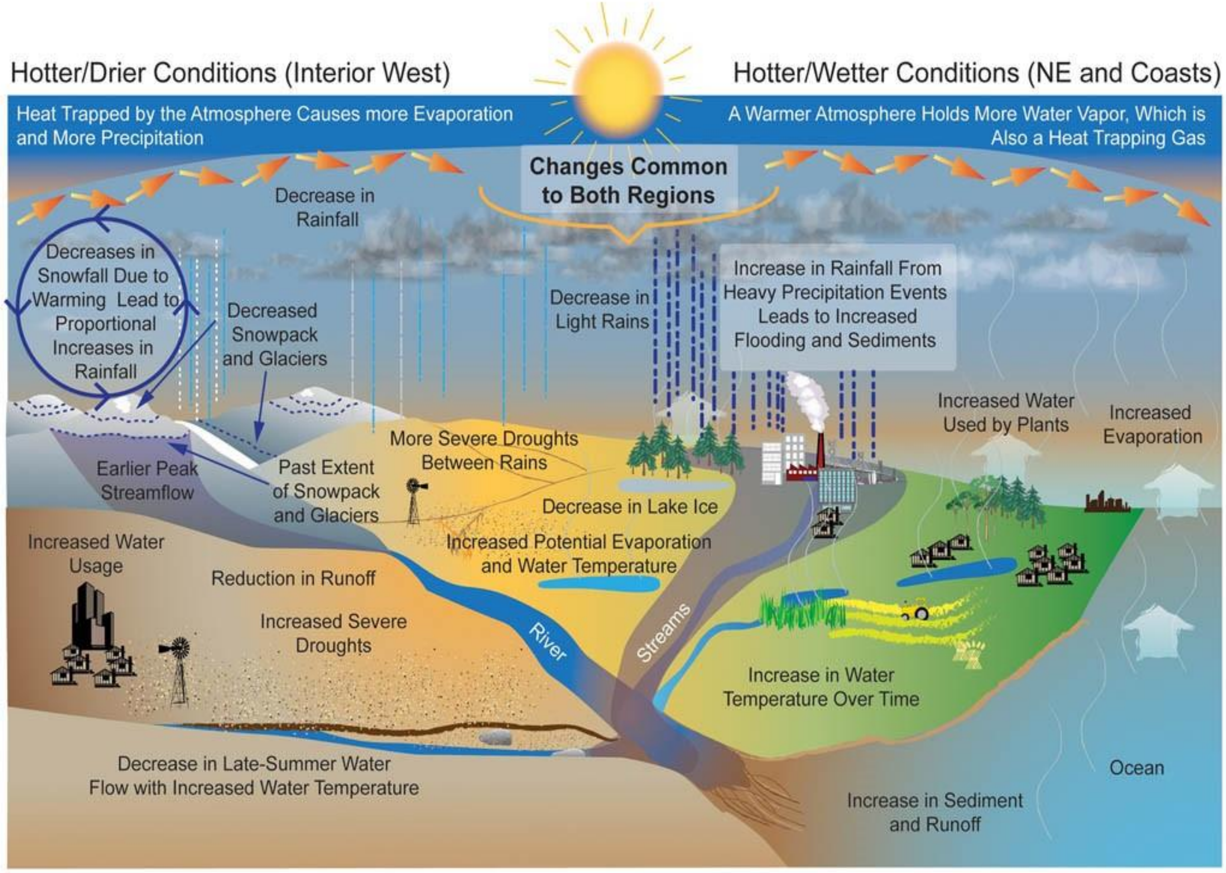

Figure 2. 8: Climate Change Impacts on Water Resources. (Adopted from United State Global Change Research Program – USGCRP, 2009).

2.6.1 Impacts of Climate Change on Precipitation and Streamflow

Precipitation is important for a variety of reasons., including the environment, water availability, agriculture, irrigation water, drinking water, and the creation of hydroelectric power. Climate change has an impact on precipitation's intensity, frequency, and the total amount (*Trenberth et al.,* 2007; IPCC 2013). Surface and groundwater are most likely to be impacted by changes in precipitation frequency and intensity, soil moisture, groundwater recharge, flow, reservoir volume,

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and surface runoff. Changes in precipitation patterns both spatially and temporally have an impact on a variety of issues, including water quality, quantity, resource availability, and others (Arnell and Gosling, 2016). On the other hand, changes in precipitation's amount, quality, frequency, and type affect society, the availability of water, the environment, agricultural production, the use of irrigation water, water management, and the generation of hydroelectric power. In response to climate change, the river's streamflow will change as well as the distribution of both the annual total and seasonal precipitation (Giorgi *et al.*, 2011; Elsner *et al.*, 2010; Hamlet *et al.*, 2013).

The amount of water is determined in large part by streamflow that is accessible in various locations, as well as the amount of water that is available for irrigation, drinking water, and the production of hydroelectric power. It is crucial to encourage development and make sure there is enough water during droughts. River or streamflow, however, possibly alters because of the consequences of climate change (Berghuijs *et al.*, 2014; Ejder *et al.*, 2016 a; Kale *et al.*, 2016a). Its impact also can change hydrological processes and conditions and runoff volume in a river basin which affects streamflow (Ma *et al.*, 2009). There have been numerous investigations into how climate change is affecting the current streamflow (Piao *et al.*, 2010; Gizaw *et al.*, 2017; Asadieh and Krakauer, 2017; Patil *et al.*, 2018).

The availability of water, as a result, is crucial for agriculture, irrigation, hydropower, and long-term socio-economic development. Water availability is strongly related to precipitation, climate, and the climate system. Water demand, supply, and availability may change because of the consequences of climate change, which is brought on by an increase in average temperature as a consequence of global warming (Tsanis *et al.*, 2011; IPCC, 2013;). Water distribution both spatially and temporally is climate change effects (Arnell *et al.*, 2011; Kirby *et al.*, 2016; Garner

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et al., 2017), and has the potential to shorten the wet season, raise water temperatures, and worsen water quality both inland and along the coast (Garcia-Ruiz *et al.*, 2011; Senatore *et al.,* 2011). On the other hand, these effects can impact the availability of both ground and surface water. Climate change will affect soil moisture and evapotranspiration in addition to the amount and availability of water (Elsner *et al.*, 2010; Giorgi *et al.,* 2011; Hamlet *et al.*, 2013).

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2.7 Impacts of Climate Change on Water Availability for Hydropower Generation

Hydropower is a significant source of energy and has a profound effect on people's lives. According to Watts *et al.* (2015), van Vliet *et al.* (2016), and Flörke *et al.* (2018), it offers the clean and renewable energy required for economic development. Additionally, it offers a source of power that is more dependable than current power systems (Liao *et al.,* 2018; Chung *et al.*, 2018). The most effective way to produce electricity is through hydropower, which is also very profitable and contributes to climate protection by lowering greenhouse gas emissions and using renewable energy sources. More reliance on renewable energy sources and current energy efficiency standards are two (2) of the solutions that have been proposed for the effects of climate change will be lessened with lower greenhouse gas emissions. Despite the hydropower sector's considerable efforts, the effects of climate change make it challenging to meet the current generation's expanding global and regional energy needs. This is because temperature changes, along with variations in precipitation amounts and frequency, can have a big impact on how rivers or streamflow, how much water is available, and how river basins are managed, especially in river basins where the ability to generate hydroelectricity is heavily dependent on hydrological condition (Finger *et al.,* 2012; Gaudard *et al.,* 2013; Gaudard *et al.,* 2013).

Both nationally and internationally, the production of hydropower is significantly impacted by climate change. According to Kang and Khan (2009) and Seiller and Anctil (2014), the availability of water is affected by climate change and hydropower production and may affect hydropower energy supplies. Because a direct correlation exists between the river's flow and the volume of water passing through the basin with climate change, hydroelectric power generation is at risk (Edenhofer *et al.,* 2012). In the catchment area, this river significantly contributes to the production of hydroelectric power. Changing the seasonal distribution, total, and frequency of precipitation as well as the magnitude and seasonality of streamflow may already be affected by climate change on reservoir evaporation and hydroelectric power generation. Droughts and changes in hydro-meteorological conditions brought on by climate change may harm the production of hydroelectric power (Fakhri *et al.*, 2013; Ragettli *et al.*, 2016; Kraaijenbrink *et al.*, 2017; Huss and Hock, 2018; Li *et al.*, 2020a,b; Li *et al.*, 2020b). Climate change, water flow, and supply all directly relate to one another, making this issue potentially much more challenging in the future.

2.8 Impacts of Climate Change on Water Availability for Irrigation

Irrigation is a vital tool for fostering long-term growth, financial stability, and job security. It has assisted some regions in recovering from droughts while also serving as a buffer when they occur. While offering indirect advantages like increased agricultural production, irrigation helps keep agricultural yields and productivity at a steady level. Providing water for the needs of the plant boosts food production, lowers hunger, and promotes the growth of superior plants. Future irrigation and agriculture are uncertain because of the limited, erratic, and unpredictable rainfall brought on by climate change. It is a cornerstone that supports farmers and lessens their reliance on weather patterns, allowing them to increase average agricultural production. This is influenced

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by the availability of water, which has a big impact on irrigation, agricultural productivity, and production. Additionally, it serves as a major driver for increasing agricultural production per hectare and for extending agricultural coverage. According to the FAO (2016), Fischer *et al.* (2007), Moreno-Pérez and Roldán-Caas (2013), Schultz *et al.* (2009), and Fischer *et al.* (2016), more than 70 % of irrigation water abstraction and annual water use worldwide are used for irrigation.

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Water supplies for agriculture and irrigation are significantly impacted by climate change, which has implications for food security on a national and international scale (Alcamo *et al.*, 2007). According to Solomon *et al.* (2007), Kundzewicz (2008), and IPCC (2013), this is a result of the water cycle changing. The temporal and spatial variations in the fundamental components of the water cycle have an enormous impact on hydrological processes. The sector most impacted by climate change is irrigation, which uses more water than any other industry. Conversely, the consequences of climate change, increase the rate of evaporation, which raises the demand for water for irrigation, which already consumes the most water in the current environment (Wang *et al.*, 2012; Shrestha *et al.*, 2020).

2.9 Hydrology and Hydrological Modeling

2.9.1 Hydrology

Hydrology is the science that examines how water originates, moves, and is stored within the earth's system. Penman (1961) defined hydrology as the science that studies how a precipitation event affects its surroundings. According to Ray (1975), the scientific field of hydrology studies the occurrence, distribution, and circulation of the world's freshwater resources as well as their physical and chemical characteristics and responses to their surroundings (including their interactions with biotic species). Hydrology is the study of how water resources are connected to their surroundings as they develop at each stage of the water cycle (Devi *et al.*, 2015). According to Chow *et al.* (1988), hydrology is the study of all aspects of water on earth and is crucial to both environmental sustainability and human life.

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Hydrology gives direction for the design and operation of water resource systems, planning, managing, and controlling water resources using the fundamental engineering and geographical concepts of its study area. The study of hydrology and its application has many practical applications, some of which include flood management, irrigation, hydraulic structure planning and operation, and others (McCuen, 1998; Shaw *et al.*, 2010; Khalid *et al.*, 2015). Applied hydrology is important for hydrological research to fully understand the physical and stochastic mechanisms, it is necessary to estimate the amount and quality of water in various reservoirs and phases. A variety of models have been created to predict the hydrological behavior of river basins, including models for surface and groundwater.

2.9.2 Hydrological Modeling

Hydrological modeling is the process of describing real-world hydrological systems and features using computer simulations, scaled-down physical models, and mathematical counterparts (Allaby and Allaby, 1999). Hydrological modeling is the representation of a portion of the water cycle in a condensed theoretical form (Figure 2.9). Usually, they are used in hydrological forecasting and process and cycle understanding. Hydrological models are a useful tool for investigating the variables that affect water resources. It can be used to calculate the most likely outcomes of various future scenarios. Hydrologists simulate system behavior using models to more fully grasp the processes at play and anticipate potential future events. The study of the dynamics that control intricate ecological and sustainable systems and the projection of potential effects are both made possible by hydrological modeling. A specific component of the hydrological system is conceptually represented in simplified form by hydrological models. The hydrological simulation system and modeling are presented in (Figure 2.9).

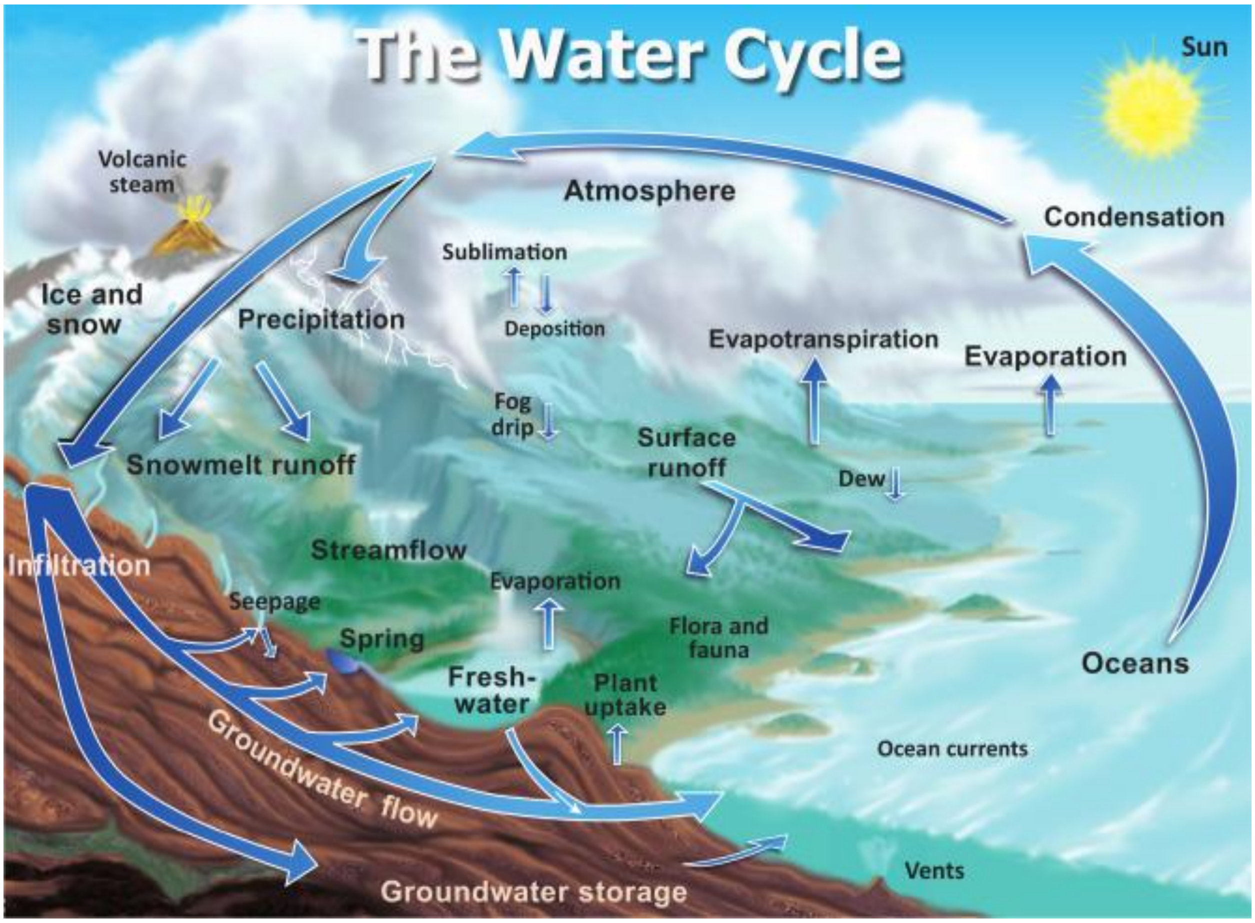

Figure 2.9 Hydrological Modelling. (Adopted from Journal of African Earth Sciences, 2016).

2.9.3 Hydrological Models

A hydrological model is a streamlined representation of a real system, water resource analysis, prediction, and management are aided by the presence of various water bodies, including groundwater, a wetland, surface water, groundwater, or an inlet (Devi *et al.*, 2015). According to Sorooshian (2008), hydrological models are simplified representations of real-world scenarios.

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Models were developed to better understand how many aspects of the climate, human development, land use, management practices, and other factors all have an impact on the hydrological cycle and hydrological processes. These models also reflect the non-linear and dynamic transformation of precipitation into runoff and flow (Kour *et al.*, 2016). According to Jajarmizadeh *et al.* (2012), these models take into account processes like the runoff and flow of both surface and groundwater, infiltration, interception, evaporation, transpiration, and melting. In line with the geography, geology, and land use of the catchment, the models, according to Devi *et al.* (2015), contain a large number of equations that calculate runoff and streamflow magnitude in the river basin. Numerous parameters can be used to modify the properties of these models

Models are used to look into how the water balance is affected by land use, climate change, and human activity. They are also used to characterize real-world processes, mimic hydrological changes, and represent and simulate real-world processes. With the aid of these models, it is possible to precisely predict, evaluate, and estimate the availability and variations in water resources over space and time, flow, runoff, and water resources in river basins, equally in terms of quantity and quality. Additionally, they are used in environmental planning, water resource management, and the design and administration of water resource systems. Recently, many hydrological models have been created globally to assess the effects of modified management practices, climatic change, and changes in land use on hydrology, water resources, water availability, streamflow, quantity, and quality of water.

2.9.4 Classification of Hydrological Models

A classification based on thematic priorities and user-oriented criteria is preferred from the perspective of the model's users. The goal of the model, the characteristics of the system to be

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modeled, the hydrological process or related variable component to be taken into account, the degree of causality of the process, and the necessary discretization in time and space. There are many advantages too, or even reasons why it may be necessary, to classify hydrological models. This is crucial for figuring out the model's availability and choosing an appropriate model for the application. Three (3) of these criteria, specifically the goal of the modeling process, the level of predictability, and the necessary discretization of time and space need more research and significant recommendations.

Hydrological models have been the subject of previous classification attempts made by several scientists Fleming (1972), Woolhiser (1973), Shaw (1983), Chow (1988), and Gosain (2009). According to Devi *et al.* (2015), there are various categories into which hydrological models can be divided based on the input parameters and application of physical models. However, according to Refsgaard (1996), depending on the process description of the system, hydrological models are three (3) types: deterministic, stochastic, and jointly stochastic-deterministic. Physically-based distributed models, conceptually lumped models, and empirical models are all examples of deterministic models (Figure 2.10).

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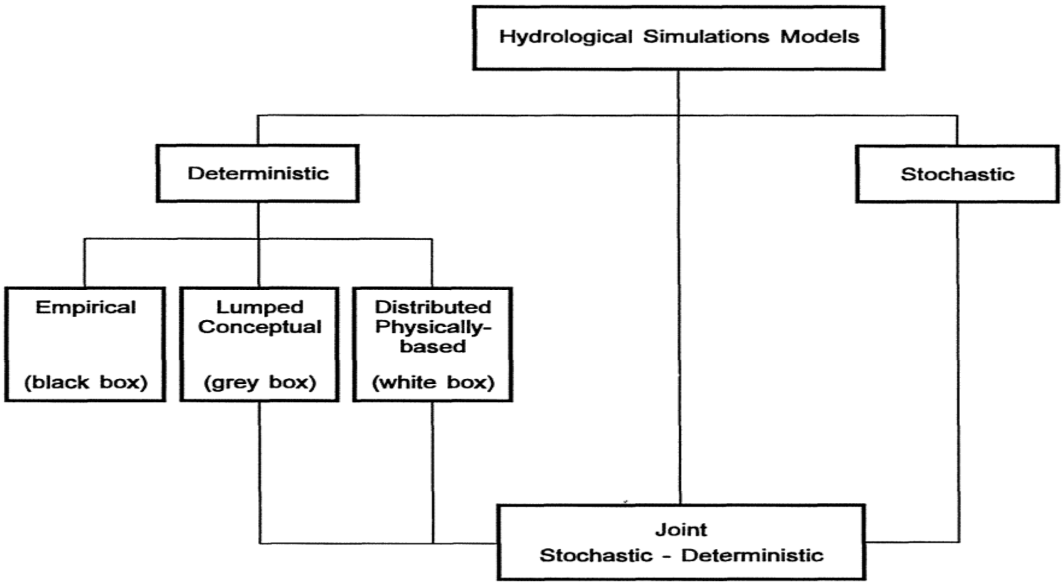

Figure 2.10: Classification of Hydrological Models. (Adopted from Refsgaard, 1996).

Both sub-categories of hydrological models are stochastic and deterministic. Deterministic models with the same entry over and over again because they do not produce randomness. The models require a lot of data and processing overhead because they use complex physical theory. In contrast, a stochastic model yields more random results. Consequently, a stochastic model makes a prediction and a deterministic model makes a forecast (Chow, 1964). Chow et al. (1988) classification of hydrological models is shown in (Figure 2.12). Figure 2.11 depicts the classification of hydrological models (Shaw, 1983). All classifications, history, parameters, inputs, and outputs of the hydrological model can be found in the details of Fleming (1972), Woolhiser (1973), Shaw (1983), Chow (1988), Refsgaard (1996), Willems (2000), Cunderlik (2003), Lewarne (2009), Gosain *et al.* (2009), and Devi *et al.* (2015).

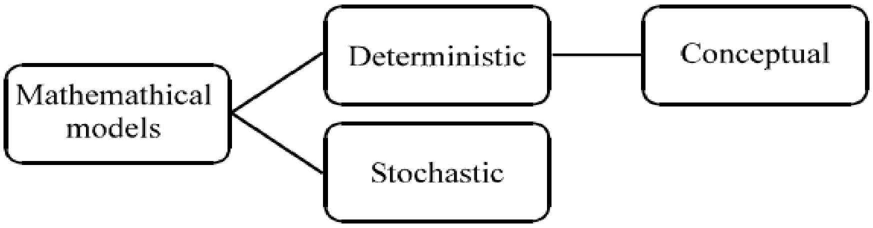

Figure 2.11: Hydrological Models Classification. (Adopted from Shaw, 1983).

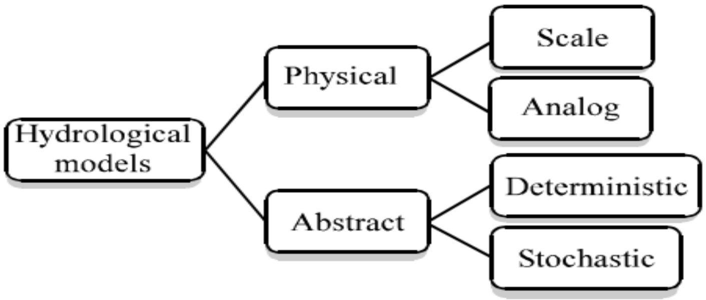

Figure 2.12: Hydrological Models Classification. (Adopted from Chow *et al.*, 1988).

2.10 Impacts of Climate Change on Hydrological Conditions - Past Studies in the Omo- Gibe River

Past studies on how climate change will impact how much water is available in the Omo-Gibe River basin have been limited. In addition, no research has been done on how the future availability of water for irrigation and hydropower generation in this basin will be impacted by climate change. In Ethiopia, however, most of the previous studies on how climate change affects water availability has been done in the Nile, Awash, and Rift River basins.

The hydrological consequences on the water regime of the Omo-Gibe Basin are evaluated by Chaemiso *et al.* (2016) using the RCM model and SWAT is assessing how climate change will impact processes that affect surface water, using baseline scenario A1B. This analysis from 1985 to 2005 revealed significant differences in seasonal and monthly precipitation as well as an

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expected rise in annual temperatures. A rising trend in annual potential evapotranspiration has also been observed for scenarios of future climate change. Surface water also changes during the seasons, in the dry season, the mean monthly runoff was lower; in the wet season, it was higher Future percentage changes in seasonal and annual hydrological variables showed increasing patterns.

The IWMI Global Environmental flow calculator and hydrologic alteration indicators were used by Tesfaye *et al.* (2020) to forecast how environmental flow indicators in Ethiopia's Omo-Gibe Basin will be affected by climate change. This study discovered that climate change has an impact on the flow regimes of ecosystems and various water sectors, impacting ecological communities, and paving the way for the introduction of non-native species. Future changes in the flow regimens may reduce ecosystem biodiversity and species richness.

The spatiotemporal hydroclimatic variability the Anose *et al.* (2021) studied the Ethiopian Omo-Gibe River basin using the information on precipitation and temperature, and flow collected between 1981 and 2014. With the help of the Sen dip estimator and the Mann-Kendall trend test, the study looked at the spatial and temporal variability of hydroclimatic variables in the Omo-Gibe River basin. The findings showed a significant rise in seasonal and annual mean temperatures over the previous 20 years. Precipitation in the basin exhibits low to moderate seasonal and monthly space-time variability. Over the past 20 years, the basin has experienced variations in discharge and flow.

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2.11 Global Adaptation Options to Climate Change and Coping with the Impacts of Climate Change

The two primary global responses to climate change are mitigation and adaptation, both of which are essential to resolving the issue and illustrating ways to combat climate change. In order to slow climate change and reduce the likelihood of extreme events, mitigation strategies are needed, to decrease GHG concentrations by reducing greenhouse gas emissions and increasing carbon sinks (IPCC 2001; Lu 2013). "Climate mitigation measures" are actions that reduce the amount of heat-trapping greenhouse gases within the atmosphere. In order to achieve this, emissions from sources like the use of carbon-based fuels for transportation can be reduced, by heating, and electricity, or by reducing the amount of these gases already in the atmosphere by improving "sinks" for these gases, such as soils, forests, and oceans. The goal of mitigating climate change, according to a 2014 IPCC report, is "to stabilize greenhouse gas levels long enough to give ecosystems time to adjust to climate change naturally in order to guaranty that food production won't be negatively impacted and make sustainable economic growth possible."

Adaptation means regulatory strategies implemented in response to a real or projected climate stimulus (IPCC, 2001; Pan and Zheng, 2010; IPCC, 2014). The definition of adaptation includes the modification or alteration of natural or human systems, etc., for a specific purpose, as well as the reduction of vulnerability or the enhancement of resilience to counteract the effects of climate change that are already occurring or that will presumably happen. The method of coping with climate change to current or predicted climatic conditions. Reduced exposure to the harmful effects of climate change is the aim, for instance, the rise in sea levels, the escalation of weather catastrophes, and the rise in food insecurity. Utilizing all the potential advantages of this covers climate change effects like lengthened growing seasons or, in some places, higher yields.

2.12 The Present Study is Unique from Previous Research

In comparison to past studies, the current study is unique.

i) There has not been any evaluation or research done on future precipitation change indicators.

- ❖ Climate change causes changes in the seasonal distribution and annual precipitation totals, and these changes have a significant impact on streamflow.

ii) Climate change has effects on future water supplies that have not been quantified or fully understood, which affect irrigation and the production of hydroelectric power.

- ❖ It is critical to assess and understand how climate change will impact the amount of water that will be available in this basin in the future for irrigation and the generation of hydroelectric power. For the purpose of lessening the effects of climate change, long-term management of water resources as well as the development of adaptation and mitigation plans are crucial.

iii) There are no studies or identified adaptation strategies for climate change.

- ❖ Appropriate climate adaptation measures would be required to lessen the impact of climate change on the available water for irrigation in the future and the production of hydroelectric power.

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CHAPTER THREE

MATERIALS AND METHODS

3. 1 Study Area

Omo-Gibe River basin is among the river basin's most important and second-largest river basins in Ethiopia. Hydroelectric power plants and the basin's most important resources are large-scale irrigation projects. Its coordinates are 4°30N to 9°30N and 35°E to 38°E in southwest Ethiopia. The basin's surface area is about 79,000 km^2, and the river empties into Lake Turkana (Figure 3.1). The basin is shared equally between the Oromiya and the Region of Nations, Nationalities, and Peoples of the South (SNNPR); each region receives approximately 25 to 75 % of the basin (ITABCONSULT DFC, 2001). This basin is home to around 14,580,516 people (Ethiopia Census, 2017). Rain-fed agriculture is a major part of a river basin economy.

There are differences in annual precipitation, with the southern lowlands receiving less than 400 mm/year and the highlands receiving 1900 mm/year. The lowlands typically have temperatures above 29°C, while the uplands typically have temperatures of 17°C (Woodroofe *et al.,* 1996; Degefu and Bewk *et al.*, 2014). A single peak can also be seen in the basin and two (2) unimodal seasonal precipitation distributions in the north and middle and a bimodal distribution in the south. In contrast to spring, which occasionally experiences rainy weather, usually dry and warm, winter, and autumn. In the basin, it rains a lot more during the summer. Yearly flow on average through an estimated 16.9 billion cubic meters makes up the basin (FAO, 2016), which corresponds to every year, 14% of the nation's surface water resources are used (Woodroofe *et al.*, 1996). Plateaus and lowlands make up the basin's varied topography (Worku *et al.,* 2014). The plateaus have an average elevation of and occupy 51% of the basin at an elevation of 2800 meters above sea level

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(m a.s.l.). While the lower Omo plain is located at an altitude of 400 to 500 meters above sea level, the northern and central plateaus have terrain that is above 1500. m.a.s.l. The basin's source waters are located at the highest altitude of 3,360 .m.a.s.l (Woodroof and associates, 1996; Worku et al., 2014).

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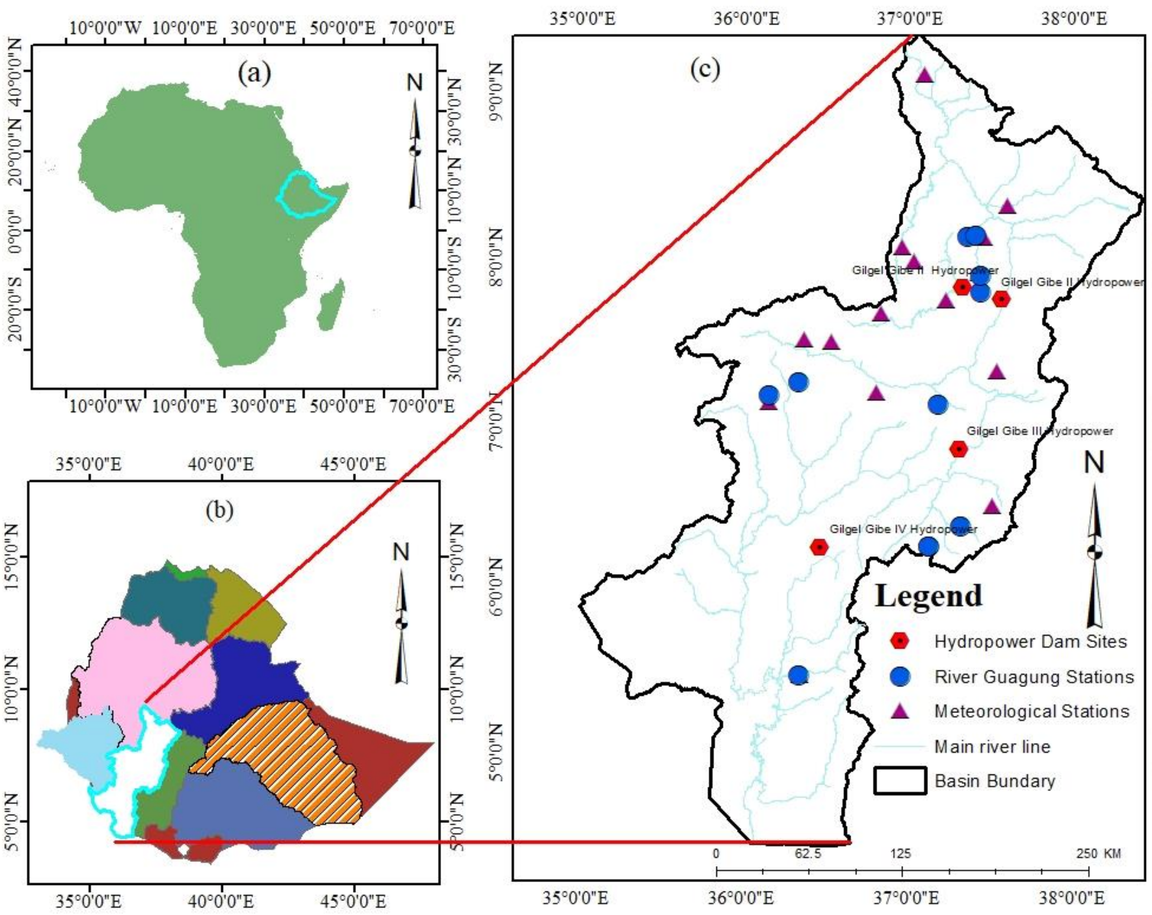

Figure 3.1: Location Map of the Study area (a) Africa map (b) Ethiopia's Major River Basins and (c) Omo-Gibe River Basin. (Author’s Construct, 2022).

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3.2 Materials

3.2.1 Hydroclimate Data Homogeneity Test

Levene's test method then was done using the Statistical Package for the Social Sciences (SPSS) to identify and remove inhomogeneous stations for this study's trend analysis of hydroclimatic variables (Brown and Forsythe, 1974).

3.2.2 Hydroclimate Data Consistency Test

Consistent hydroclimate data means that the all-time series collected belong to the same statistical population. Inconsistency and non-stationarity, on the other hand, imply that all recorded time series data belong to different populations. The cause of the problem is anthropogenic climate change and changes in land use. Making sure that hydroclimatic data is consistent before conducting research into the effects of climate change is one of the most important things for managing the present and future water resources.

Using the double mass curve method, the consistency test of the hydroclimatic data used in this study was validated (Mu *et al.,* 2010). The foundation of the double mass curve theory is the observation that, provided that the proportionality between the two quantities remains constant, a straight line can be drawn by tracing them over the same period. The proportionality is then represented by the angle at which the line slopes. With the help of this technique, a time series can be smoothed and its hydroclimatic data can be made free of random elements.

The cumulative totals for that set are compared to equivalent cumulative totals for a representative sample of nearby sets to determine whether the data is accurate. To ensure uniformity among all

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climate variables stations, the double mass curve was applied. All of the selected stations were used for this study and climate change projection because the results were consistent across all of the stations.

3.2.3 Hydroclimate Missing Data Filling

The objective of filling out missing values or records in the hydroclimate data is to ensure that the information does not contain missing values or records. Missing data gaps are observed in recorded hydroclimatic data a common problem with hydroclimatic data in developing countries. It has an impact on the quality of the results obtained during hydroclimatic studies, the accuracy of trend estimation, distributed hydrological modeling, and the management of water resources. Inconsistency and gaps in available hydroclimatic data are mainly due to the temporary absence of observers, measurement instrument failures, errors in recording observations, extreme weather events, infrequent calibration of sensors, and difficulties in accessing measurement areas (Kashani and Dinpashoh, 2012). Therefore, an appropriate filling of the missing data must be applied before any analysis is conducted.

In this study, any hydroclimatic data gaps were filled using the inverse distance weighting method. Inverse distance weighting is more popular among hydro-climate scientists due to its simplicity (Hubbard, 1994). The missing value is estimated using distance-weighted average data from neighboring stations (Cressman, 1959; Shepard, 1968). This equation is used to compute missing values (Eq. 3.1).

$$M_o \frac{\sum_{i=1}^{n} \frac{M_I}{D_I}}{\sum_{i=1}^{n} \frac{1}{D_I}} \qquad \text{Eq 3.1}$$

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where M_0 is the estimated missing value, M_i is the value of the same variable at the i^{th} station and d_i is the distance between the target station and the i^{th} surrounding the station. However, the quality of the estimation is determined by the radius of influence rather than by the weighting function (Tronci *et al.*, 1986). Although neither station in our study area is more than 100 km apart, (Tronci *et al.*, 1986 and Xiao *et al.*, 1999) suggested a 100 km influence radius.

3.2.4 Reference Periods Hydroclimate Data Sets

Daily reference information was gathered for the river basin from the National Meteorological Agency (NMA) between 1980 and 2019 and included rainfall, minimum and maximum temperatures, sunshine hours, humidity, and wind speed. The Ethiopian Ministry of Water, Irrigation, and Electricity (MoWIE) provided information on the daily base streamflow for comparison, model calibration, and validation of the periods 1986–2019. Throughout this study, more than twenty-two precipitation stations and twenty temperature stations' daily data were collected (Table 3.1). Fifteen temperature and precipitation gauge station data were used for hydrological input after the consistency and homogeneity test. Data on it was recorded on the amount of sunshine, wind speed, and relative humidity for each of the four (4) stations collected. After checking the homogeneity and consistency of the data, the hydrological model as input was chosen in two (2) of each. Thirteen (13) measuring stations' streamflow data were collected from the basin (Table 3.2). Only the streamflow data from a single measuring model's calibration and validation were done at the station after the data's homogeneity and consistency tests were evaluated.

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Table 3.1: Rainfall and Temperature Gauging Stations and Locations in the Study Area.

Name of Gauge Station	Record Period	Latitude	Longitude	Elevation (m)
Agaro	1995-2019	7°85'	36° 56'	1669
Assandabo	1986-2019	7° 76'	37° 23'	1764
Bako	1986-2019	9°12'	37° 05'	1650
Bonga	1986-2019	7°28'	36° 24'	1599
Gidole	1986-2019	5°65'	37° 37'	1431
Hossana	1980-2019	7°57'	37° 86'	2306
Jimma	1986-2019	7°67'	36° 82'	1710
Jinka	1980-2019	5°78'	36° 56'	1373
Konso	1986-2019	7°34'	37° 44'	2087
Limugenet	1986-2019	8° 07'	36° 95'	1767
Seku	1990-2019	7°68'	40° 20'	2471
Shebe	1986-2019	7° 51'	36° 52'	1921
Wiliso	1986-2019	8° 55'	37° 98'	2058
Wolaita	1986-2019	6° 82'	37° 75'	1854
Wolikete	1986-2019	8° 28'	37° 77'	1888

Source: National Meteorological Agency (NMA) of Ethiopia. (Collected, 2020)

Table 3.2: Streamflow Gauge Stations and Locations in the Study Area

Station name	Record period	Latitude	Longitude	Area sq km
Ajancho near Areka soke river above Ajora fall (2)	1995-2015	7° 8'	37° 43'	
Demie Orota Alem	1987-2006	6° 38'	37° 31'	1866
Dincha at Bonga	1990-2014	7° 12'	37° 17'	190
Great Gibe Abelti	1980-2015	8° 14'	37° 35'	15746
Guma near Andaracha	1990-1913	7° 9'	36° 15'	443
Ghibe nrear Baco	1990- 2015	9° 7'	37° 33'	288.1
Gojeb Chida	2002-2014	6° 26'	37° 12'	937
Gojeb near Shebe	1990-2013	7° 25'	36° 32'	3577
Mazie near Morka	1980-2015	6° 26'	37° 12'	
Nerie near Jinka	1980-2015	5° 47'	36° 33'	166
Sheta at Bonga	1990-2016	7° 17'	36° 14'	937
Sokie near Areka	1987-2015	7° 9'	37° 43'	103
Wabi near Wolkite	1985-2007	8° 15'	37° 4'	231

Source: Ministry of Water, Irrigation, and Electricity (MoWIE) of Ethiopia. (Collected, 2020)

3.2.5 Input Data Sets of the WEAP Model

The WEAP model's input information, which was utilized to evaluate how climate change will impact future water availability for irrigation and hydropower generation, is displayed in (Table 3.3).

Table 3.3: Input Data Used for the WEAP Model.

Data Type	Source	Description
Hydrology	MoWIE	Shapefile of reservoirs and all water distributions
Irrigation area, hydropower and reservoirs, and Environmental flow data	MoWIE, Oromia Irrigation Development Authority (OIDA), SNNPRS Irrigation Development and Schemes Administration Agency (IDSDAA), and Ethiopian Electric Power Corporation (EEPCO)	Shape and Excel file format
Water demand and consumption	MoWIE, Omo-Gibe Master Plan, and survey data, strategic documents, reports	Irrigation, domestic, hydropower, industrial, commercial, livestock, recreational, institutional, and business
Potential Evapotranspiration	FAO (Sogreah, 2010), MoWIE, Omo-Gibe Master Plan, and strategic documents	22,300 mm/year
Social-economic data	MoWIE and the Central Statistics Agency of Ethiopia (CSA)	Current and projected population growth rates (2017-2100)

Sources: MoWIE, OIDA, Omo-Gibe Master Plan, EEPCO, ISDAA, CSA and IDSDAA. (Collected, 2020)

3.2.6 Geographic Spatial Data Sets

Land use/land cover map, a soil map, and DEM, three (3) spatial data maps were utilized in this study. These spatial data sets were used to project future water availability for irrigation and hydroelectric power generation as well as to evaluate the heterogeneity of river basins. The 30-

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meter-by-30-meter Aster DEM was used and was downloaded from https://glovis.usgs.gov/app. It was used to input layer configuration, extract the slope of the flow network, determine the flow direction, accumulate the sub-basin parameters, and calculate the characteristics of the sub-basin, as shown in (Figure 3.2a). A map of digital land use or land cover type was used to reflect the river basin's heterogeneity, prepare land use databases and extract land use properties and landcover categories of thirteen dominant land use types (Figure 3.2b). A soil map was used to reflect the river basin's heterogeneity, prepare soil databases to generate soil properties, and extract soil properties and categories of thirteen (13) major soil types (Figure.3 2c). The WEAP model employed spatial input data to compute the basin's water supply, demand, and available balance. Others were used for WEAP model reservoir data, which all contribute to water supply, demand data, irrigation, domestic, hydropower, industrial, commercial, livestock, recreational, institutional, and business data, supplementary information on socioeconomic population, household, and livestock growth rates (Table 3.3).

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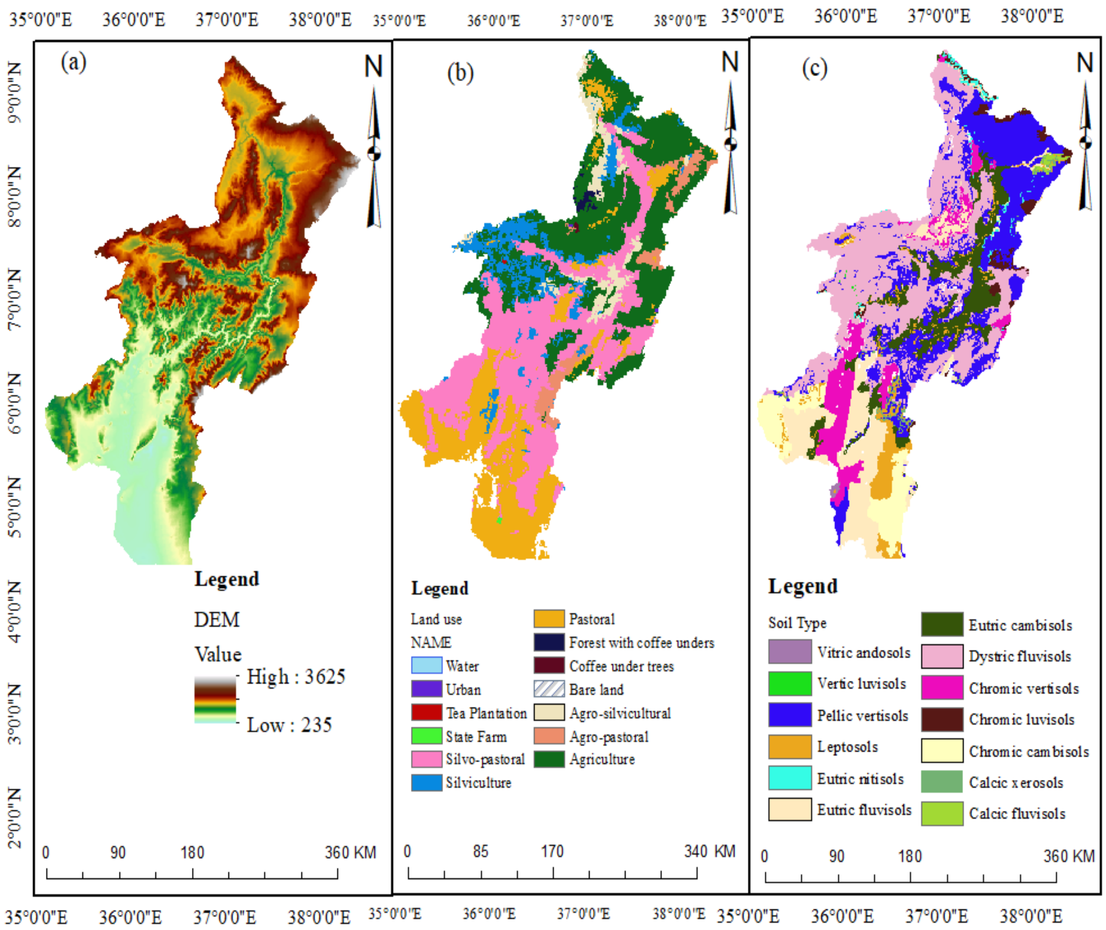

Figure 3.2: The Study Area (a) DEM, (b) Major Land use / Landcover Map types, and (c) Major Soil Types Map of the Study Area. (Author's Construct, 2022).

3.2.7 Hydro-Meteorological Input Data

Climate data is needed to analyze climate variables and input data for the hydrological model for SWAT and WEAP model simulations and evaluate the streamflow magnitude and subsequent water availability of the baseline period to be compared with the streamflow magnitude and subsequent water availability in future periods. The basin's climate data, which covered the years 1987 to 2019, was used. This included information on daily humidity, wind speed, precipitation, and sunshine hours, and maximum and minimum temperatures. Streamflow data is required a reference period is needed for the model's validation and calibration for determining how climate change is affecting streamflow. Between 1997 and 2019, data on the basin's daily observed streamflow were used as models for validation and calibration.

3.2.8 Future Climate Change Scenario Data Sets

For the century's end in the twenty-first (2017–2100), data on daily precipitation, and minimum-maximum temperatures were projected. These data were predicted under the emission scenarios RCP8.5 and RCP4.5, according to Taylor *et al*. (2012)'s CMIP5. Eleven (11) different GCMs and sixteen (16) RCMs were used to project the effects of climate change (Table 3.4). Climate projections were made using the CORDEX-Africa. Predicted temperature and precipitation data were used as output variables in the hydrological model. It is necessary to quantify and forecast the impacts of climate change on the future availability of water used for irrigation and hydropower production by the turn of the twenty-first century (2017–2100) for future streamflow simulations are required. Future time, precipitation, and temperature data for the RCP8.5 and RCP4.5 emission scenarios were downloaded using the CMIP5 model from (https://pcmdi.llnl.gov/mips/cmip5/dataportal.html// node portal of the IPCC database distribution center). In September 2021, all data, including historical data, were accessed.

3.3 Methods

3.3.1 Representative Concentration Pathways (RCPs) Climate Change Emission Scenarios and Assumptions Scenarios

A plausible prediction of the upcoming climate is a climate scenario based on a group of climate-related connections and radiative forcing assumptions that are inherently consistent, even though

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it is frequently oversimplified. It is common practice to produce inputs specifically for models that model climate change's impacts. The IPCC published the Representative Pathway Scenarios (RCPs), a set of speculative scenarios, in 2013. According to Taylor *et al.* (2011), scenarios have been added to CMIP5 to improve the climate change assessment, adaptation, and protection against the effects of climate change. These scenarios replace the Special Report on Emissions Scenarios (SRES) climate model projections. These trajectory scenarios were developed to serve to cause both short-term and long-term impacts of climate change by acting as the primary driving force modeling studies and as an accurate forecast of future climate conditions, such as precipitation, temperature, and other climate variables (van Vuuren *et al.*, 2011a). It is based on many fundamental presumptions about growth, socio-ecological change, economic development, use of land, population growth, use of energy, advancement of technology, etc. (Kriegler et al., 2013). The multi-model collection includes simulations of the changing climate in the twenty-first century using four different RCP scenarios as well as extensions of the projections of the changing climate from 2100 to 2300 using the emission scenario of RCP (van Vuuren *et al.*, 2011a). Four different RCP scenarios estimate that by the year 2100, radiative forcing will be a significant factor: RCP2.6 RCP8.5, RCP4.5, and RCP6, (Thomson *et al.*, 2011; Masui *et al.*, 2011; Riahi *et al.*, 2011; van Vuuren et al., 2011). These radiative forcing values were predicted by the potential effects of climate change discussed in the fifth assessment report of the IPCC for climate change (IPCC, 2014), and they were associated with pathways where greenhouse gas emissions concentrations were at pre-industrial levels. RCP 2.6 only produces a very small number of emissions. The assumption that environmental progress will lead to improved behavior is presumptuous. On the other hand, the emission scenario RCP 8.5 has a very high level of emissions. By the year 2100, greenhouse gas it is anticipated that emissions will rise as a result of human activity such as

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deforestation, shifting land uses, and the burning of fossil fuels as well as natural phenomena such as respiration and volcanic eruptions. RCP 4.5 and 6.0 will be in decline in the year 2100, which will mark the 20th century coming to an end.

Indicators of radiative forcing for greenhouse gases in the RCPs, which range from 2.6 to 8.5 W/ m^2, are representative of a range for that year. If the RCP2.6 scenario were to occur (van Vuuren *et al.,* 2011b), the mitigation scenario leads to a shallow forcing level which is qualified as a hypothetical, "optimistic," scenario with low levels and concentrations of greenhouse gas emissions and one that mandates a level of less than 2.6 W/m^2 by 2100. Median range or stabilization scenarios RCP4.5 (Thomson *et al.,* 2011) which includes various technologies and regulations to lower greenhouse gas emissions, with radiation from stables reaching 4.5 W/m^2 by 2100 and RCP 6. 0 scenarios also an average range or stabilization scenarios (Masui *et al.*, 2011) predict stalls of 6 W/ m^2. According to projections made by Riahi *et al.* (2011), RCP 8.5 would be the worst-case scenario, which is the highest level anticipated to be produced of corporate or high-level emissions and GHG emissions, with projected emission levels of 8.5 W/m^2. This scenario is a socio-economic climate policy that will cause the atmospheric concentration of greenhouse gases to rise; as emissions increase gases from industrial growth and urbanization by chance, the temperature will rise sharply, and precipitation will decrease. Due to economic and demographic growth, water demand in the upcoming decades will rise. This study projected future climate change using the RCP8.5 and RCP4.5 scenarios and many other economic, population, land use, and energy consumption hypotheses late in the twenty-first century (Tapiador *et al.*, 2019).

3.3.2 Global Climate Change Models

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General circulation models (GCMs), also known as Global climate models (GCMs) are the natural systems of the Earth that are represented numerically as well as physical simulations of constitute the climate system's primary components (Solomon *et al.*, 2007; Alley *et al.*, 2007). Models are crucial tools for accurately predicting changes in climate brought on by rising concentrations of greenhouse gases and simulating reactions to their emissions and are used to understand and predict current and upcoming local, national, and global climate conditions and systems. (IPCC, 2007). According to Flato *et al.* (2013), these models are crucial for simulating, evaluating, and simulating climate change conditions and climate change-related variables, like variations in precipitation and temperature, and how they relate to greenhouse gas concentrations.

GCMs, continue to be the primary source of projections of possible future climate changes for understanding global climate change (Edwards, 2011; IPCC, 2013). The CMIP5 archive provides the number of GCMs used for climate prediction and impact assessment that are currently available (Taylor *et al.*, 2012; IPCC, 2013). Precipitation and temperature are examples of climate variables that can be predicted using a climate model for the year 2100 based on RCP8.5 RCP2.6, RCP4.5, and RCP6 climate scenarios (Masui *et al.*, 2011; Riahi *et al.*, 2011; Thomson *et al.*, 2011; van Vuuren *et al.*, 2011; IPCC, 2014). These models are the potential to project the global effects of greenhouse gas concentrations, climate change, climate variability, volcanic eruptions, and other factors.

An improved understanding of the global climate is made possible by the GCM model's data (Solomon *et al.*, 2007; IPCC, 2013). For use in planning for adaptation, making local or regional decisions, or conducting impact assessment studies, the GCM's output is too coarse-scale approximate (>100 km). GCMs are more difficult to use for local-scale impact assessment studies

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because of their coarse resolution and worsening biases and uncertainties as scales change regionally, then locally, then globally (Joetzjer *et al.*, 2013; Lutz *et al.*, 2016; Gebrechorkos *et al.*, 2019). According to Tavakol *et al.* (2013) and Dixon *et al.* (2016), downscaling climate projections will improve spatial resolution and eliminate bias before they are used for impact assessments and adaptation planning. Many techniques have been developed by climatologists to convert coarse-resolution climate change estimates produced by GCM into fine-resolution climate projections, addressing the inherent limitations of GCM results for fine-scale applications (Hidalgo *et al.*, 2008; Abatzoglou and Brown, 2012).

Higher resolution downscaled products from Reginal Climate Models (RCMs) are often used for accurate and detailed climate information needed to assess climate change impact on a regional scale. This is because RCMs have better resolution in the 10 – 50 km range (Mariotti *et al.*, 2014), they take into account the local heterogeneity (Gbobaniyi, 2014) and the land surface in a region with complicated topography (Endris, 2013). RCMs models provide regional information in greater detail than GCMs models and climate information on much finer spatial scales than GCMs (Buontempo *et al.*, 2015; Dosio *et al.*, 2015). Through investigation of climate change's effects preparation for and the reduction of its effects at the regional level, and assessment of its impacts, these regional climate models can support successful adaptation to climate change.

This study demonstrates that using multiple GCMs and RCMs can help reduce uncertainty about potential futures and be more accurate when estimating and forecasting climate change impacts than using a single GCM and RCM discipline. Analysis and evaluation of the effects of climate change are more credible when multiple GCMs and RCMs are used. The CORDEX-Africa RCMs models and the GCMs models that drive them are listed in (Table 3.4) for this study. The driving

GCMs and RCMS models were selected for the current study based on the requirement that results must be comparable between emission scenarios and an ensemble of models that predict a wide range of climate variables, including temperature and precipitation. Additionally, previously conducted Ethiopian performance studies (Bekele *et al.*, 2018; Musie *et al.*, 2020) and in Africa, the Horn of Africa (Osima *et al.*, 2018) had been taken into account. In August 2021, the complete set of climate data was accessed. Future climate change projections from using the climate data pots (https://pcmdi.llnl.gov/mips/cmip5/dataportal.html//) were downloaded.

Table 3.4: List of CMIP5 Models CORDEX Africa RCMs, their Driving GCMs Downscaled.

No	Institution	Driving GCM	RCM	Ensemble	Model Domain	Resolution
1	Canadian Center for Climate Modeling and Analysis (Canada)	CCCma-CanESM2	CCCma-CanRCM4 and SMHI-RCA4	r1i1p1	Africa – Cordex	0.44°
2	Centre National de Recherches Météorologiques and Centre Européen de Recherche et Formation Avancée en Calcul Scientifique/CNRM-CERFACS France	CNRM-CERFACS-CNRM-CM5	SMHI-RCA4	r1i1p1	Africa – Cordex	0.44°
3	Commonwealth Scientific and Industrial Research Organisation/Organisation/CSIRO Australia	CSIRO-QCCCE-CSIRO-Mk3-6-0	SMHI-RCA4	r1i1p1	Africa – Cordex	0.44°
4	Iirsh Center for High-End Computing (ICHEC)	ICHEC-EC-EARTH	EC-EARTH DMI-HIRHAM5, SMHI-RCA4, and KNMI-RACOM22T	r3i1p1, r1i1p1, r12i1p1	Africa – Cordex	0.44°

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5	Institut Pierre-Simon Laplace/IPSL France	IPSL-IPSL-CM5A-LR	SMHI-RCA4	r1i1p1	Africa – Cordex	0.44^o
6	Institut Pierre-Simon Laplace/IPSL France	IPSL-IPSL-CM5A-MR	SMHI-RCA4	r1i1p1	Africa – Cordex	0.44^o
7	Max Planck Institute for Meteorology/MPI-M Germany	MPI-M-MPI-ESM-LR	SMHI-RCA4 and UQAM-CRCM5	r1i1p1	Africa – Cordex	0.44^o
8	National Institute for Environmental Studies, and Japan Agency for Marine-Earth Science and Technology (MIROC), Japan	MIROC-MIROC5	SMHI-RCA4	r1i1p1	Africa – Cordex	0.44^o
9	Met Office Hadley Centre/MOHC UK	MOHC-HadGEM 2-ES	SMHI-RCA4	r1i1p1	Africa – Cordex	0.44^o
10	Geophysical Fluid Dynamics Laboratory/GFDL USA	NOAA-GFDL-GFDL-ESM2M	SMHI-RCA4	r1i1p1	Africa – Cordex	0.44^o
11	Norwegian Climate Centre/NCC Norway	NorESM 1-M	SMHI-RCA4	r1i1p1	Africa – Cordex	0.44^o

Sources: GCMs are Downscaled by each RCM. Adopted from WCRP and https://pcmdi.llnl.gov /mips/cmip5/dataportal.html, 2013).

3.3.3 Coordinated Regional Downscaling Experiment (CORDEX)

The climate experimentation program CORDEX is run as a project of the World Climate Research Program (WCRP), to provide compressed regional climate data sets for all areas of the world. High-resolution climate data processing and archiving are firstly focused on the climate of Africa (Nikulin *et al.*, 2012). According to Tiepolo *et al.* (2017), CORDEX will create a collection of various dynamic and statistical downscaling models that take the GCM multiple enforcement of the CMIP5 file into account. In order to encourage the study of adaptation and the consequences of climate change by the AR5 timeframe and beyond, CORDEX improves global projections for climate change on a regional scale (Tiepolo *et al.*, 2017).

For this study, daily time intervals for the historical temperature and precipitation data (1951-2005) and future temperature and precipitation projections (2006-2100) were downloaded. Future datasets were predicted using the RCP8.5 and RCP4.5 emission scenarios from the IPCC CMIP5 (Moss *et al.*, 2010). Eleven (11) driven GCMs and fifteen (15) different CORDEX-RCMs models were used from CMIP5 (Tayler *et al.*, 2012; IPCC, 2013) to project data, as shown in (Table 3.4).

3.3.4 Climate Variable Data Downscaling

The post-processing of GCM data, or "downscaling," from large-scale GCM to small-scale RCM, has been developed for use in regional research, evaluations of the effects of climate change, decision-making, and climate change adaptation initiatives on a local level. The output of the GCM cannot be used with the hydrologic models because of the coarse spatial and temporal scales. Small-scale downscaled data on the climate's various variables, including precipitation and temperature, are needed for hydrological models and can be obtained by downscaling from GCM to RCM. These climate variables downscaling strongly affected hydrological simulations and evaluation; due to this, the output of the GCMs cannot be used directly for local impact studies. The output of GCM is too coarse spatial resolution (250 by 250 km) data to be used directly as input for a hydrologic model that reduces climatic variables representation at the regional and river basin scale. The output data from the RCM model is more realistic as an input to a hydrological model than the output data from the GCM model (Dessu and Melesse, 2013). This necessitates the need for downscaling in studies of the effects of climate change at the regional and river basin scales.

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There are several methods of downscaling. Statistics and dynamic downscaling methods are widely used to overcome limitations of the coarse resolution, aiming to bridge the gap between low spatial resolution and low-resolution information provided by GCMs and local climate information. The effects of climate change on the river streamflow and the availability of water in the river basin must be assessed and understood.

Dynamic downscaling includes a nested RCM suitable for areas with complex terrain and very uneven vegetation cover (Kimball *et al.*, 2017; Walton *et al.*, 2018). However, statistical downscaling affects large-scale predictive fields from a GCM up to small-scale predictive scaling techniques that can be used to statistically relate the GCM to variability derived from local time-series data (Cibin *et al.*, 2010; Ayar *et al.*, 2015; Berg *et al.*, 2015; Ochoa *et al.*, 2016; Olsson *et al.*, 2016). Large-scale connections are feasible atmospheric predictor climate variables to regional and river basin scale climate data time series. Downscaled river basin climate variables, temperature simulators, and precipitation simulators are used in regional climate models (RCMs) developed as part of the CORDEX Africa climate project program. This regional climate model, created by the WCRP, is a CORDEX Africa domain that has been experimentally explicitly established for climate studies and the evaluation of climate impacts on Africa.

Compared with dynamic downscaling methods, regional climate model simulations statistical downscaling is computationally undemanding and cheap, more cost-effective, and fitness-for-purpose for many local scale applications. According to Asong *et al.* (2016) and Tiwari *et al.* (2019), statistical downscaling uses less computing power and can be completed quickly. This method works based on standard statistical procedures and can generate point-scale climate variables from data on the GCM scale. Its computational efficiency is also very high. The

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calculation only takes a small part of the time. However, Dynamic downscaling requires sophisticated computing resources and takes a lot of time (Brown *et al.*, 2017, Li *et al.*, 2020). As a result, it is not feasible to perform dynamic downscaling in the required area.

3.3.5 Removal of Bias from Projected Climate Data

The most robust bias correction strategy was needed to adjust climate variables produced by RCM using observational data before developing future climate change scenarios for impact assessment research on climate-related cases (Christensen *et al.*, 2008). Impact models are usually calibrated against observations, such as in hydrology, agriculture, ecology, etc. Since model discrepancies often (or are biased) from these facts, direct application of climate model results to impact models could lead to unnecessary results (for instance in the case of the hydrological model (Grouillet *et al.*, 2016). Differences between statistical distributions of actual and simulated series are often used to describe the biases in climate models (Vaittinada *et al.*, 2021)**.**

The output temperature and precipitation data from the RCMs in this study were corrected using the Quantile mapping (QM) method (Mpelasoka and Chiew, 2009). According to Sennikovs (2009), Teutschbein and Seibert (2010), and Teutschbein and Seibert (2012), the approach has as its goal of matching the RCM value's distribution function to the distribution function of the observed values for the time frame of comparison. According to Tpánek et al. (2016), this bias adjustment technique performs better than other bias correction methods in adjusting the precipitation, temperature, and other variables that are among the output frequencies from RCMs. It is also the most acceptable and best method currently available for removing bias from climatic variables for fitting raw RCMs results. Also, the method is a well-known approach (Han *et al.*, 2018; Yang *et al.*, 2018). RCM climate data were corrected for bias with temperature and

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precipitation data from fifteen (15) gauging stations following consistency and homogeneity testing respectively stations are shown in (Table 3.1).

3.3.6 Climate Change Adaptation and Coping Strategies

In responding to future climate change and potential strategies for reducing its effects are adaptation and mitigation strategies. Adaptation is the process of effectively altering recent or anticipated climatic shocks and their effects to increase resilience, reduce harm, and reduce vulnerability to climate change (IPPC, 2014b). Its strategies are adjusting the systems or expected climatic stimuli (Pan and Zheng, 2010) for future climate change while mitigation strategies are reducing GHG emissions from the atmosphere, and increasing sinks of carbon and greenhouse gases (Lu, 2013). Mitigation describes the procedures followed to reduce greenhouse gas emissions (IPPC, 2014; IPPC, 2014c; IPPC, 2014d)

The primary issue of mitigation strategies is an international reduction of carbon dioxide emissions (Lu, 2013). It provides a long-term slow process and global benefits with increasing carbon sinks (Duguma *et al.*, 2014a; Swart and Raes, 2007). The primary issue of adaptation strategies is a local and river basin scale providing short-term and regional benefits the adaptation strategies (Duguma *et al.*, 2014b; Swart and Raes, 2007) are a priority for climate change impact reduction. Even though there are more benefits associated with mitigation and adaptation than there are drawbacks, these two strategies differ from one another in terms of their qualities, advantages over one, and limitations. Who decides their goals or objectives, bears the cost, and reaps the benefits of mitigation and adaptation differ from those who benefit from them, and both have lots of evidence to back them up (Wilbanks *et al.*, 2003; Klein *et al.*, 2005; Locatelli *et al.*, 2011).

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In this study, adaptation strategies were employed to manage water resources for hydropower production, irrigation, and other anticipated climate change effects, as well as to address the problem of increasing water demand and decreasing water availability (Jiménez Cisneros et al., 2014).

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3.3.7 Mann-Kendall (MK) Trend Test

This study employed a nonparametric trend testing technique known as the MK trend test (Kendall, 1975) to determine whether a trend was present in this study. Changes in hydroclimatic variables were analyzed, their statistical significance was assessed, and their presence or absence of a trend was determined. It has several advantages, including a lower sensitivity to outliers, and the ability to the absence of enough input data for a given distribution when applied to time series data (Ebrahimian et al., 2018; Mondel et al., 2015).

All long-term hydroclimatic variable trends must be examined, and past, present, and anticipated changes must be confirmed to predict how climate change brought on increasing levels of greenhouse gases in the Earth's atmosphere are responsible for climate change will behave in the future. This study accepted significance levels of statistical analysis of the data and the null hypothesis for the (1987–2019) reference period periods and future periods of three (3) windows: short-term (2017-2044), medium-term (2045-2072), and long-term (2073-2100) and examined streamflow, precipitation, and temperature distributions over time as well as in different seasons using the two-tailed homogeneity test of the R programming language.

If H0 is present, the data series does not exhibit a monotonic trend. A continuous monotonic trend in the data series is indicated by HA. The test statistics and distributional properties were compared to decide if the null hypothesis should be believed or disbelieved. Rejecting the null hypothesis and the Type I error is maintained at less than or equal to 5% or 10% of the normal distribution if Z's absolute value is greater than its critical value, which relates to a specific type of error. For a particular significance level (0.05 or 0.1), they were typically obtained using tables and software. The critical value for Z1/2 was determined by the standard normal table to be 1.96 with a p-value of (0.05 or 0.1).

Tests on trends in streamflow, temperature, and precipitation that have been observed and forecast were evaluated Z-scores are used to determine the significance levels for these data (standard deviation), and the p-value (probability) and an absolute confidence level value are both used of -1, 0.96, and + 1.96, respectively. These values fall within the range of 0.05 and 95% of the degree of the confidence interval. Whether 0.05 is the minimum or maximum value for the p-value determines whether the null hypothesis is accepted or disregarded. At the 0.05 level, the significance of the observed statistics and evaluated streamflow simulations and predictions, as well as projected and bias-corrected temperature and precipitation. The MK Series statistic (Var[S]) and the Z-Test statistic over time are calculated using the following standard mathematical formulas: Equation (Eq.3.2) can be used to calculate the variance of the corrected links assuming that the data contain p-value links as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \mathrm{sgn}(x_j - x_i) \qquad \text{Eq. 3.2}$$

Where n is the number of data points, xi and xj are the data values in time series i and j (j > i), respectively, and sign (xj – xi) is the sign function as

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$$\mathrm{Sgn}(\mathrm{Xi}-\mathrm{Xj}) = \begin{cases} +1, (x_j - x_i) > 0 \\ 0,\ (x_j - x_i) = 0 \\ -1, (x_j - x_i) < 1 \end{cases} \qquad \text{Eq. 3.3}$$

$$E[S] = 0$$

$$\mathrm{Var}[S] = \frac{\left\{n(n-1)(2n+5) - \sum_{J=1}^{q} t_p(t_p-1)(2t_p+5\right\}}{18} \qquad \text{Eq. 3.4}$$

$$Z_s = \begin{cases} \frac{S-1}{\sqrt{VAR(S)}}, & \text{if } S > 0 \\ 0, & \text{if } S = 0 \\ \frac{S+1}{\sqrt{[VAR(S)}}, & \text{if } S <= 0 \end{cases} \qquad \text{Eq. 3.5}$$

In these equations, X_i and X_j represent the time-series observations in chronological order, n represents the length of the time series, t_p represents the number of ties for the p^{th} value, and q represents the number of tied values.

While negative Z values in the same series that show a downward trend indicate a decreasing trend, positive Z values in the hydrometeorological time series indicate an increasing trend; Negative. To identify changes in streamflow, precipitation, and temperature, the software packages "Trend" and "Kendall" R Libraries were employed. Furthermore, these programs evaluated the statistical significance of the change. Hydrometeorological time series data can be evaluated to determine whether they increase, decrease, or remain constant over time using this pattern analysis and pattern recognition method (R Core Team, 2017). Using a GitHub project, the author's version was compared to all trend analysis and detection, historical time series analysis of trend reversals and reversal points (Patakamuri and Brien 2019; Patakamuri, 2019). These comprehensive R archive network (CRAN) package libraries are available for free download and include in-depth user

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manuals. Through the GitHub version control system and the CRAN repository, they are available to the general public. Utilizing each trend analysis, the interface's numerical and mathematical plotting was created.

3.3.8 SWAT Hydrological Model

In this study, river streamflow and, subsequently, total water availability estimates in the basin during reference periods and future periods under future climate change scenarios were evaluated and simulated using the SWAT model. This was done by integrating with ArcGIS-ArcView extension and interface ArcSWAT (version 2012). SWAT is a distributed, physics and process-based, time-continuous, spatially adaptable, dynamic, time-continuous (annual, monthly, and daily) model at the basin scale that replicates many variables' daily time stages over long time scales (Arnold *et al.*, 1998; Arnold *et al.*, 2012; Neitsch *et al.*, 2011).

The SWAT model is capable of simulating a situation on a regional scale and estimating hydrologic cycles and hydrologic processes, river flow, water quantity, and quality, both surface and underground (Neitsch et al., 2011). In the model, surface runoff is simulated using techniques from Green and Ampt (1911) and Soil Conservation Service (1972). This study employed the SCS-CN method, which is a modified version of the Soil Conservation Service Curve Number method to determine how much surface runoff is caused by daily precipitation. The potential evapotranspiration model is estimated using the methods described by Penman (1948), Monteith (1965), Priestley and Taylor (1972), and Hargreaves and Samani (1985). The daily potential evapotranspiration was calculated using Penman-Monteith as a reference period. In order for the model to calculate daily evapotranspiration potential, it needs to be aware of the humidity, wind speed, ambient air temperature, and solar radiation. The Hargreaves method was used to determine

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the daily evapotranspiration potential for upcoming periods. According to Arnold *et al.* (2012), the Hargreaves method is used to calculate potential evapotranspiration using only temperature and precipitation data. The model simulates the network of river channels using two (2) different approaches: the Muskingum method (Chow, 1964) and the variable accumulation coefficient method (William, 1969). For this study, the simulated data were produced using the Muskingum method (Neitsch et al., 2005; Neitsch et al., 2011; Arnold et al., 2012b) providing additional details and an explanation of how the SWAT model used the spatial and climate data. You can access input data, model development, simulations, and estimation techniques on the SWAT model's website (http://swatmodel.tamu.edu), as well as Neitsch et al. (2005), Gassman et al. (2007), Neitsch *et al.* (2011), and Arnold *et al.* (2012), to name a few examples. The model is used to calculate the water balance for each HRU and river basin using daily data. The water balance equation is used in the model to simulate the daily hydrology of the HRU and basin (Eq. 2) (Neitsch et al., 2011).

$$SW_t = SW_o + \sum_{i=1}^{t} (R_{day} - Q_{surf} - E_a - W_{seep} - Q_{gw}) \qquad \text{Eq. 3.6}$$

where SW_t is the final soil water content (mm); SW_0 is the initial soil water content on day i (mm); t is time (days); R_{day} is the amount of precipitation on day I (mm); Q_{surf} is the amount of surface runoff on day I (mm); E_a is the amount of evapotranspiration on day I (mm); W_{seep} is the amount of water entering the vadose zone from the soil profile on day i (mm); $Q_{gw}$is the amount of return flow on day i (mm) (Neitsch *et al.*, 2011).

The SWAT hydrological model was chosen and used for this investigation because it is trustworthy and adaptable enough to function with the current baseline and upcoming continuous simulation

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indicator tools for assessing how hydrology and water availability will be affected by climate change, river streamflow, climate impact studies, and understanding catchment area change (Schuol and Abbaspour, 2007; Keshta *et al.*, 2009; Alansi *et al.*, 2009; Cibin *et al.*, 2010; Bae *et al.*, 2011; Ficklin *et al.*, 2012; Bessa Santos *et al.*, 2019; RivasTabares *et al.*, 2019). The system's compatibility with existing analysis data and tools is another factor. It accurately captures information on the climate now and in the future, as well as the river basin's drainage characteristics. It also has the potential to represent scales of high spatial resolution. The model is also a well-known and widely used hydrological modeling tool that has been applied to forecast future streamflow variations in the river basin and water resources throughout the world (Coffey *et al.*, 2016; Yuan *et al.*, 2019; Khan *et al.*, 2020).

3.3.8.1 SWAT Model Uncertainty Analysis, Calibration, and Validation

A sophisticated computer program called SWAT-CUP (SWAT-Calibration and Uncertainty Programs) was created by Abbaspur *et al.* (2007) to evaluate the calibration, validation, and the SWAT model's lack of certainty. There are five different optimization algorithms linked to the program: Semi-Automatic Sequence Uncertainty Correction (SUFI-2), Particle Swarm Optimization (POS), General Probability Uncertainty Estimation (GLUE), Parameter Solution (ParaSol), and Monte Carlo Chain of Marks (MCMC). For the procedure, a detailed description of the SWAT-CUP computer program and the five-strategy optimization algorithm (SUFI-2, GLUE, MCMC, POS, and ParaSol) can be found (AbbAspour, 2004; AbbAspour, 2007; AbbAspour, 2015; AbbAspour 2018, 2015). Users can perform analyses on the SWAT model's calibration, validation, and uncertainty using the tools integrated with the SWAT model application

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(Abbaspour et al., 2018; Abbaspour et al., 2020). Since the application is in the public domain, anyone may use it and copy it without restriction.

This study used the SWAT-CUP-SUFI-2 Version 2019 optimization method to assess the calibration, validation, and uncertainty analysis of the SWAT model. Effectively using the SWAT model's output results necessitates performing uncertainty analysis, model calibration, and validation. Considering that the model's input parameters must be kept within a tolerable margin of error when evaluating the effects of climate change, they are process-based. Algorithmic programs for optimizing SUFI-2 are developed (Abbaspour, 1997). A programme is a tool for evaluating results by analyzing the extent of the overall structure of model uncertainties, parameter uncertainties, all sources of parameter uncertainty, uncertainties in production sources, and observed data sources (Abbaspour, 1997; Abbaspour, 2004). The SWAT model is expected to provide information on the observed, soil type, climate, land use and parameters, and data. The SWAT model and the SUFI-2 application are combined during the uncertainty assessment (Abbaspur, 2015). Two (2) main factors serve as primary indicators of uncertainty. The p factor, also known as the 95% predictor uncertainty (95PPU), is used to express the simulation uncertainty. The 95PPU band's mean depth and the observed data's standard error are divided by one another to produce the R factor, which is another tool for assessing the stability of an uncertainty run or calibration. According to Abbaspour (2004), Abbaspour (2007), and Abbaspour (2015), The appropriate values for the P-factor and R-factor are ">0.7" and "1.5," respectively

Model calibration changes the value of a set of standard model parameters by comparing predictive model outcomes to minimize predictive uncertainty. Moreover, improve performance through a range of established criteria. It is accomplished by carefully selecting the model's most sensitive

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parameters (Arnold *et al.,* 2012). A method for choosing the best values for the most sensitive model parameters is called parameter optimization (Immek, 2003; imnek *et al.,* 2012). Model calibration's main goal is to obtain the optimal values for the unknown parameters of the model. If a model accurately represents observable data, it is said to be calibrated (Moriasi *et al.,* 2007; Moriasi *et al.*, 2015).

A model's effectiveness is independently evaluated during validation. During this process, the model is used with input parameters that were predetermined and kept constant during the calibration process. After the calibration procedure has been compared to the remaining observational data, the model is validated using data that weren't incorporated into the calibration procedure to guarantee that the model's predictions are correct. To ensure that the observed streamflow data are time-divided and that the streamflow data used for calibration and validation do not significantly differ from one another. Observed dry, moderate, and wet years are measured at stations in both periods (Ganand et al., 1997). In contrast to the calibration period, the daily and monthly streamflow are predicted during the validation phase (Wilson, 2002). Model checking, according to Refsgaard (1997), is the process of proving a model's validity in one location and its ability to generate simulation models in another with "sufficiently specific speeds," although what constitutes "specific enough" can change depending on the objective.

The SUFI-2 algorithm was used for this study because it has expanded the most popularity and is extensively used for parameterization, sensitivity, uncertainty analysis, calibration, and validation, among these algorithms (SUFI-2, GLUE, MCMC, POS, and ParaSol) (Abbaspour *et al.,* 2007). The algorithm represents most of the sources of uncertainty and is easy to determine, use and maintain. It allows for greater flexibility in selecting calibration factors, such as calibrated

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parameters and intervals, times, and sub-basins, and is based on several major past research series guidelines. The algorithm's simplicity and to produce a reliable prediction, only a few model runs are necessary. It has been widely used to calibrate the large-scale SWAT model (Yang *et al.*, 2008). Since there are many parameters available to model water balance, streamflow, water resources, and availability, using the SUFI2 algorithm for it makes the most sense to analyze uncertainties, calibrate the system, and validate the SWAT model.

3.3.9 WEAP Hydrological Model

WEAP is a tool for integrating decision-making into water resource management systems (Yates *et al.*, 2005a; Yates *et al.*, 2005; Yates *et al.*, 2005b; Sieber and Purkey, 2007). To represent the anticipated basin estimate, integrated hydrological models are required and the budget is based on water availability (water supply), water demand, and water allocation (Hao *et al.*, 2015; Yaykiran *et al.*, 2019). It is a semi-theoretical, semi-distributed, continuous-time, deterministic hydrologic system model with an integrated approach to water system simulation work and strategic direction (Yates *et al.*, 2005a; Sieber, 2006; Purkey *et al.*, 2008). The Stockholm Environment Institute (SEI), a Boston-based organization, developed it, in Massachusetts, according to van Loon and Droogers (2006). The model simulates, investigates, and functions using water balance methods, making it possible to model a single basin or a complicated transboundary river basin system (Yates *et al.*, 2005; Sieber and Purkey, 2007). A tool has the potential to show the schematization of the physical system and the types of models of hydrological processes (Yates *et al.*, 2005; Sieber and Purkey, 2007; Seiber and Purkey, 2015). It represents the sources of water supply, such as groundwater, surface water, streamflow, and reservoir water, as well as water transfers, such as water demand and abstraction and transmission, such as irrigation demand, hydropower demand,

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municipal and industrial demand, etc (SEI, 2013). The WEAP model can also create and analyze a variety of future scenarios based on different hypotheses regarding the effects of demand and availability strategies for water (Yates *et al.*, 2005).

In this study, the basin's future water demand, allocation, and availability were simulated, estimated, and projected using the WEAP model. This model can map both the present and the future of various socioeconomic and climate change scenarios and their effects on water resources. (Hum and Talib, 2016). With a view to the long-term administration of water resources, the creation of alternatives, and the development of alternatives and plans for coping with climate change, it is crucial. The model uses standard linear programming at each time step of the analysis to resolve water resource allocation problems for integrated water resource planning for a variety of water resource systems. The model also simulates hydrological processes like an infiltration, evapotranspiration, snow runoff, snow melting, snow accumulation, glaciers, surface water, streamflow, reservoir water, groundwater, etc (SEI, 2013). Water demand, such as hydropower, irrigation, urban development, water flows, and hydraulic infrastructures, such as hydroelectric barriers and basin inter-diversions, river basins, and canals, are all represented (SEI, 2013). In addition, it depicts water sources like groundwater, surface water, river flows, and reservoir levels as well as water transfers like demand, catchment, transmission, irrigation, hydroelectric power, municipal and industrial demand, etc. (SEI, 2013). The WEAP model is built on the equilibrium equation of water supply and demand, which the model automatically resolves every month. Each model node calculates and assesses the site requirements and water supply according to the input requirements specified by the user monthly through a linear program. WEAP's month-over-month water accounting relies primarily on mass stability calculations that take general inputs, general

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outputs, and storage of reservoirs and aquifers. It functions according to a monthly level water balance equation (Eq. 3.7).

$$\Sigma Q inflow - \Sigma Q\ outflow - \Sigma\ Additional\ total\ Qstorage = 0 \quad \text{Eq 3.7}$$

where Q inflow is the total of inbound flows into a node and all connected inbound links; Qoutflow is the total of outgoing flows on a node and all connected outgoing links; Qstorage is the amount of storage minus any storage variant (reservoirs and aquifers)

Only reservoirs and aquifers are used as AdditionToQStorage. AdditionToQStorage is positive when storage is increasing and negative when storage is decreasing. Usage and losses are taken into account in the consumption and losses.

The WEAP model was selected for this study because it offers a thorough, flexible, and straightforward framework in order to assess, plan, and analyze water resources strategically. In comparison to other water allocation models, the tool has gained the most recognition globally (Yates et al., 2009). Additionally, policies guiding future water availability must be informed by planning and management tools for water resource management.

3.3.10 Prediction of Water Demand and Water Allocation for Irrigation and Hydropower Generation Under Future Climate Change Scenarios

The integrative SWAT-WEAP modeling approach simulated and calculated water balances in this study using this method as well as project water availability, demand, and allocation for future irrigation and hydroelectric generation. Integrated model simulations are required to estimate water users' balancing, demand, and management (Hao *et al.*, 2015; Yaykiran *et al.*, 2019). These models, estimates, and projections look at the climate change may affect how much water is

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available for irrigation and hydropower generation in the future across the river basin. The links between supply and demand under various future socio-economic and climatic changes and the evolution of water consumption conditions scenarios were also evaluated. This WEAP model's output mainly focuses on simulations of the water balance of river basins, future changes in streamflow magnitude, and the resulting changes in water availability. To meet these future demands, water planners and policymakers must design adequate water resource policies and adaptive solutions for future climate change. The purpose of the current study was to determine how future climate change would affect the amount of water that would be available for irrigation and hydroelectric power production.

The main water consumers and competing suppliers of water demand in the Omo-Gibe River basin are irrigation, domestic, hydroelectric, industrial and commercial, livestock, recreational, institutional, and business. Current and projected water demand was estimated based on the current MoWIE, OIDA, SNNPRS, ISDAA, EEPCO, and CSA; all adopted and utilized data are described in detail and briefly presented in (Table 3.3). The simulation, estimation, and projection of water availability (water supply), water demand, and water allocation might be required in the future, depending on factors like population growth and the expansion of irrigation areas, increase in hydropower, livestock increase, industrial and commercial, recreational, and institute and business increase, and changing climate. These estimates and predictions for the future availability of water were achieved through the development of climate projections, future climate change will have an impact on the Omo-Gibe River basin through a number of temperature and precipitation changes as well as the creation of climate change scenarios with hydrological simulations and projections.

3.3.11 SWAT and WEAP Model Performance Evaluation

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SWAT-CUP-SUFI-2 offers a multitude of objective functional measures for measuring model performance evaluation indicator criteria concerning the SWAT model performance evaluation indicator criteria. Statistics were used in this study to determine the Nash-Sutcliffe efficiency (NSE), coefficient (R^2), and percentage of bias (PBIAS) using the performance evaluation indicator criteria for the SWAT and WEAP model. Equations 3.8, 3.9, and 3.10, respectively, were used to determine the statistical significance levels for NS, R^2, and PBIAS. Applying the 0–1 ranged Nash–Sutcliffe efficiency value (Nash and Sutcliffe, 1970), equation 3.8 is employed to calculate the model performance assessment.

$$NS = 1 - \frac{\Sigma_i (Q_m - Q_s)2_i}{\Sigma_i (Q_m - Q_s)2} \qquad \text{Eq 3.8}$$

Where, n is the total number of observations, $Q_{o,i}$ and $Q_{s,i}$ are the observed and simulated discharge at the ith observation, respectively, and Q_{mean} is the mean observed data over the simulation period.

The coefficient of determination is used and the model performance score was determined (Eq. 3.9).

$$R^2 = -\frac{[\Sigma_i (Q_m - Q_s)\Sigma_i (Q_m - Q_s)]2}{\Sigma_i (Q_{m,i} - Q_s)2\Sigma_i (Q_{m,i} - Q_s)2} \qquad \text{Eq 3.9}$$

Where Q is discharged, Q_{mi}, and O_s are initially the measured and simulated discharge, respectively.

The typical tendency for simulated values to be either higher or lower than actual data values was determined using PBIAS to analyze model performance statistically (Gupta *et al.,* 1999). The model performs better with less PBIAS. In contrast to positive and negative values denote the model being overestimated or underestimated, respectively, the best value is zero (Zhang et al., 2011). The PBIAS equation (Eq. 3.10) is displayed below.

$$PBIAS=\frac{\sum_{i=1}^{n}(Q_{obs}-Q_{sim})}{\sum_{i=1}^{n}Q_{Obs,i}}*100 \qquad \text{Eq 3.10}$$

Where Q is discharge, Q_{mi}, and O_s are initially the observed and simulated discharge, respectively.

A model of standards and measures for assessing performance was developed by (Moriasi et al. 2015). In (Table 3.5), the statistical performance of the SWAT and WEAP models is calibrated and validated.

Table 3.5: Model Performance Assessment and Statistical Measures of Criteria.

Performance	**NSE**	**R^2**	**PBIAS**
Very Good	$0.75 < NSE \leq 1$	$0.5 < NSE \leq 0$	$PBIAS < \pm 10$
Good	$0.65 < NSE \leq 0.75$	$0.5 < NSE \leq 0.6$	$\pm 10 \leq PBIAS < \pm 15$
Satisfactory	$0.5 < NSE \leq 0.65$	$0.6 < RSR \leq 0.7$	$\pm 15 \leq PBIAS < \pm 25$
Unsatisfactory	$NSE \leq 0.5$	$RSR > 0.7$	$PBIAS \geq \pm 25$

Source: Moriasi *et al.*, (2007**).**

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CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Results

4.1.1 SWAT Model Calibration and Validation

A key hydrological variable, streamflow, can be used to forecast how the hydrological cycle and process in a river basin will respond to impending climatic changes. Data on observed streamflow were obtained from the Omo Gibe Great Abilite gauging station site. The SWAT model was successfully calibrated and validated using streamflow parameters (Appendix 2). The calibration of the model was carried out using parameter values for twenty-one (21) streamflow parameters (Appendix 2). The selection and application of calibration parameters and hydrological conditions are based on streamflow. These were picked out of the literature due to the significance of the streamflow and water availability factors, as well as for model calibration and uncertainty analysis. The most crucial streamflow parameters have been changed in accordance with (Arnold et al., 2012a), as well as those that are most sensitive to variations in streamflow magnitude. The names, explanations, and definitions of the calibrated streamflow parameters of the river basin are listed in (Appendix 2) by Mutenyo et al. (2013), Wu et al. (2012) and Cibin et al. (2010).

In this study, the SWAT model's calibration and validation were carried out using the observed mean monthly streamflow. The model was calibrated and verified using observed mean streamflow from dry, moderate, and wet years during the study periods. Using data from the years (1987 to 2019), the first model could be run, and the system's initial values for the input and output variables should be used. A two-year warm-up period was also maintained. The hydrological

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model lacks information on the initial simulation setting, which is an important realization. According to Li et al. (2015), the model needs to warm up before being used.

The validation period of the model was six (6) years of observed streamflow from 2013 to 2019, while the calibration period was fifteen (15) years, from 1997 to 2012. The model's simulation of the streamflow was accurate when it was calibrated and validated, according to the data. Additionally, the metrics and data used to assess the model's efficacy as well as the outcomes of the indicators P-factor, R-factor, NSE, R^2, and PBIAS, calibration, and validation were 0.83, 0.84, 4.2,0.35, and 0.26; and 0.84,0.85,4.4,0.28 and 0.16 respectively are acceptable (Table 4.1). The model's findings and results are therefore satisfactory and acceptable. The streamflow that the model predicted and simulated decreased, this is especially true during the dry seasons of the basin, which are warmer and drier than the wet ones. Additionally, the simulated streamflow was a precise representation of the rain during these times. Based on streamflow, the SWAT model successfully predicted and water availability basin over the reference periods was simulated (Figures 4.1 and 4.2).

Table 4.1: SWAT Model Performance Criteria for the Monthly Streamflow Simulated and Observed. Source: (Author's Construct, 2022)

Model	Indices	Year	R^2	NSE	PBIAS	P-factor	R-factor
SWAT model	Calibration	1997-2012	0.83	0.84	4.2	0.35	0.26
	Validation	2013-2019	0.84	0.85	4.4	0.28	0.16

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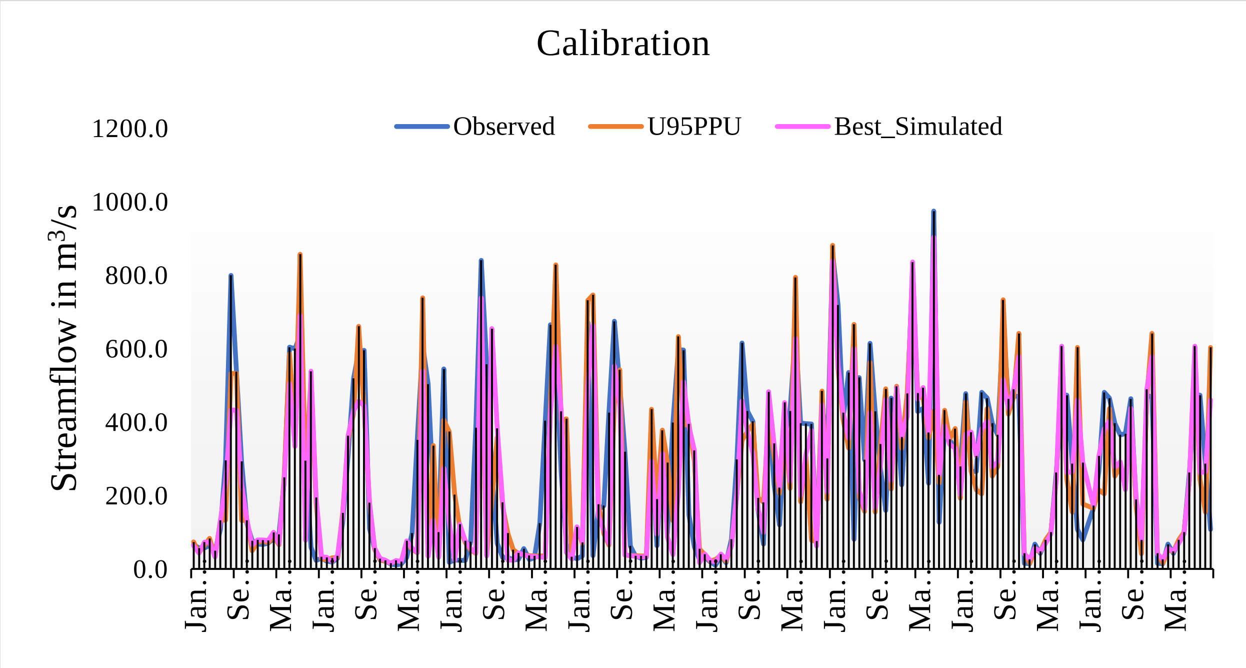

Figure 4.1: SWAT Model Calibration Observed and Simulated Streamflow Comparisons (1997-2012). (Author's construct, 2022).

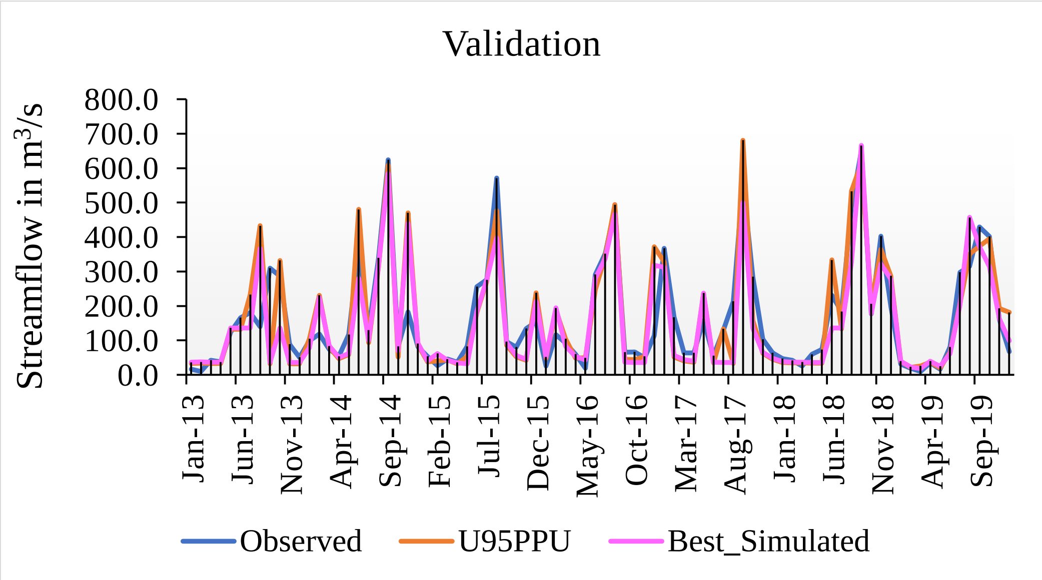

Figure 4.2: SWAT Model Validation Observed and Simulated Streamflow Comparisons (2013-2019). (Author's construct, 2022).

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4.1.2 WEAP Model Calibration and Validation

As a semi-theoretical calibration, the WEAP model requires validation for climatic effects on river flow and subsequent assessment of water availability and supply and demand estimates (Abrishamchi *et al.,* 2007). To make sure that the model results are accurate and of high quality, model validation, and calibration are required. The objective is to improve reliability and reduce uncertainties by adjusting parameters to ensure that simulated results closely match observed watershed data (Ingol-Blanco and McKinney, 2013; Ahmadaali *et al.,* 2018; Khalil *et al.,* 2018). This study evaluated how different soil types and land uses affected these hydrological and water balance processes using the Soil Moisture Model calibration method. It is the most efficient way to assess hydrological processes, water availability, and demand for satisfied and unmet water (Ingol-Blanco & McKinney, 2013; Amin *et al.,* 2018). Another reason to choose this technique was the data available for model calibration.

The parameter estimation process (PEST), created by WEAP, is regarded as the only calibration tool and consists of a calibration and validation process. The automated process allows the user to precisely adjust model parameters by comparing WEAP results to historical observations. This work used a tool for estimating non-linear PEST parameters to automatically model calibration and validation. The WEAP model utilizes and provides five (5) different calibration methods for modeling the watershed's daily or monthly hydrologic dynamics; all necessary information and methods are available at the WEAP website (http://www.weap21.org/) and (Seiber and Purkey, 2015). These methodologies allowed the selection and determination of the calibration parameters of the WEAP model by selecting and determining upper limits, lower limits, and optimal values. After calibration, hydrologic systemic conditions were validated with the objective function of the

WEAP model parameters. The model parameters accurately predicted river flow and hydrological conditions in the Omo- Gibe Basin

Observed streamflow, hydrological conditions, and system conditions were calibrated, and the WEAP model was validated using objective functions. Using the parameters, the WEAP model effectively predicted the streamflow and hydrological conditions of the Omo-Gibe basin. The best value for a parameter can be found by adjusting the parameter test error response. The Omo-Gibe Great Abilite Basin observed streamflow was utilized to calibrate and validate the model, as well as to compare simulated and observed monthly streamflow. It is critical to evaluate streamflow and hydrological conditions of baseline and future periods. In a sense, this ensures that future streamflow projections can be made with confidence under current conditions. The parameters of data on monthly mean streamflow from the periods were used to calibrate and validate the model periods 2001 to 2013 and 2014 to 2019 respectively. The results show that WEAP21 accurately captures monthly streamflow and hydrological conditions, in general, both the validation period and the independent calibration period are valid and observed against the simulated streamflow; Figures 4.3 and 4.4, respectively, depict the hydrograph of streamflow magnitudes. The model's performance indicators are displayed in (Table 4.2), which reflects this as well. R^2, NSE, and PBIAS were 0.83, 0.84, and 4.2 and 0.87, 0.84, and 4.4 during calibration and validation, respectively, highlighting the hydrograph the performance model captured (Table 4.2). On the other hand, the average bias of 2.40 m^3/s indicates a quantitative bias that was more noticeable during the calibration period than it was during the validation period and the average bias percentage when compared to the average streamflow measured. During the validation period, model performance increases, at least in comparison to bias. From 2013 to 2019, the average bias was currently only -2.5 % of the observed streamflow

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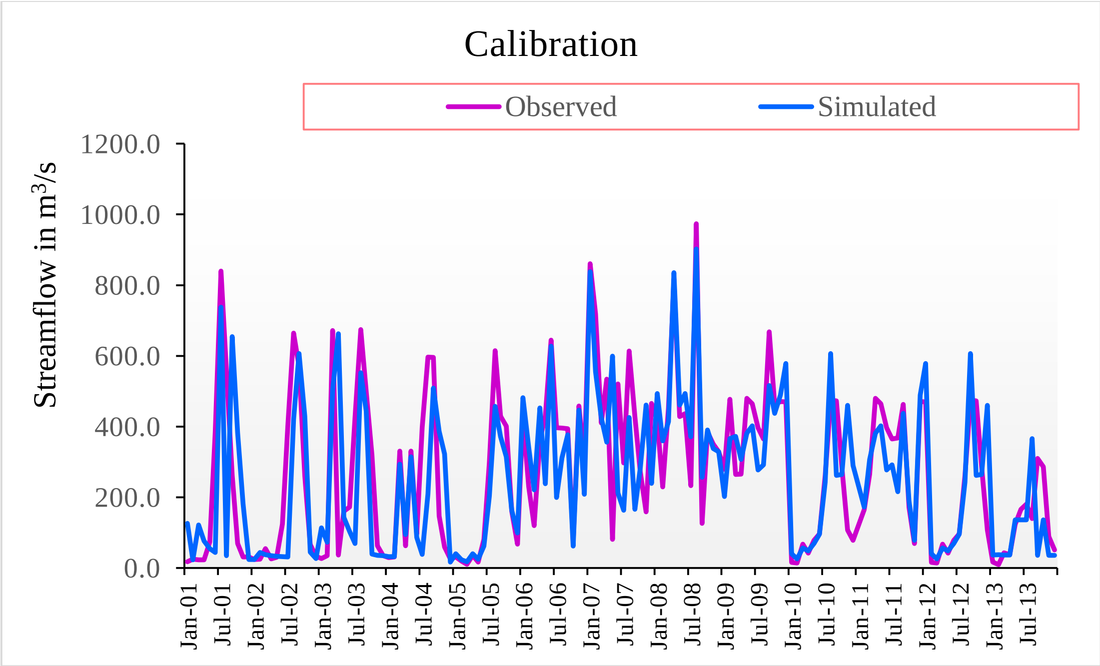

Figure 4.3: WEAP Model Calibration Observed vs. Simulated Streamflow Comparisons (2001 to 2013). (Author's construct, 2022).

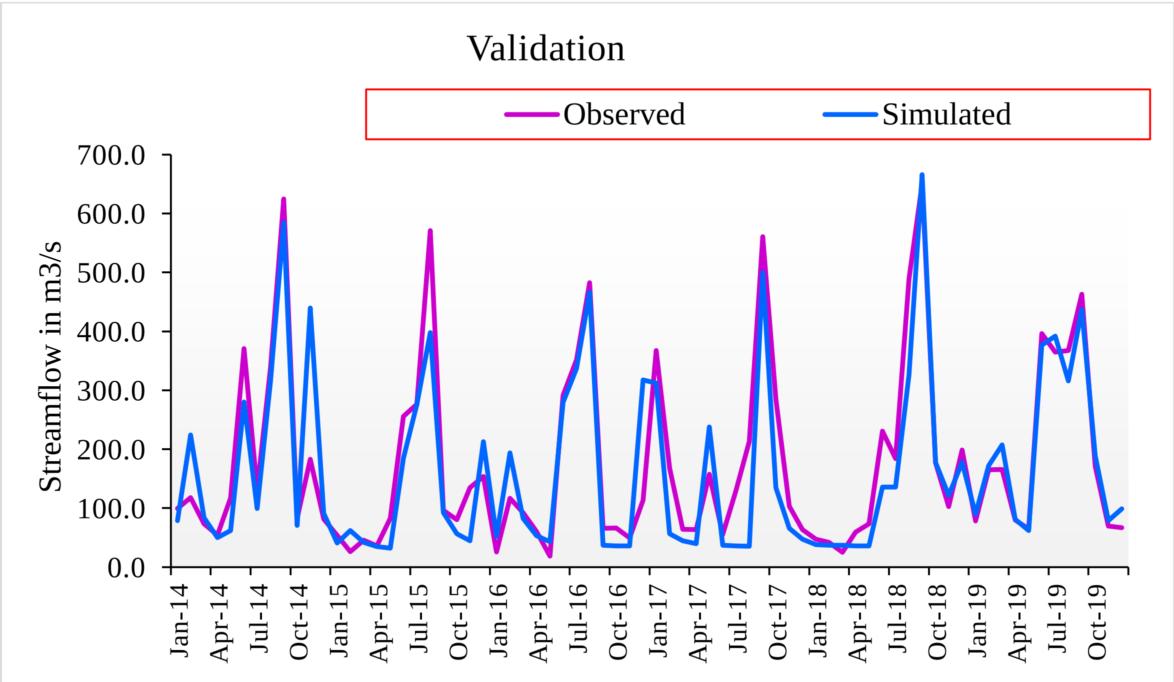

Figure 4.4: WEAP Model Validation Observed vs. Simulated Streamflow Comparisons (2014–2019). (Author's Construct, 2022).

Table 4.2: WEAP Model Performance Criteria Simulated and Observed Streamflow. Source: (Author's Construct, 2022)

Model	**Calibration and validation duration**	**Observed streamflow mean (m^3/s)**	**Simulated streamflow means (m^3/s)**	**Mean bias (m^3/s)**	**Mean bias (%)**	**R^2**	**NSE**	**PBIAS**
WEAP	Calibration 1997-2012	405.86	405.46	2.40	16.1 %	0.83	0.84	4.2
	Validation 2013-2019	404.56	402.36	-2.20	-2.5%	0.84	0.85	2.4

4.2 Observed and Projected Annual and Seasonal Hydroclimate Variables Statistically Significant Change and Trend Detection

4.2.1 Evaluation of Observed Annual and Seasonal Temperature for Statistically Significant Change and Trend Detection

Statistically significant, change and detect trends projected annual and seasonal maximum and minimum temperatures change were evaluated. Trend test results revealed baseline and projected annual and seasonal maximum and minimum temperatures statistically significantly positive increasing trends. The results of the trend tests revealed statistically significant upward trends in the minimum and maximum temperatures, both annually and seasonally at baseline and projection. Baseline fifteen (15) weather gauging stations of the Omo-Gibe Basin maximum and minimum temperatures were analyzed (1987-2019) over 32-years. The annual average and seasonal temperature change were assessed results showed a significant level (0.05) positive increasing trend at the eleven meteorological gauging stations, two (2) meteorological gauging stations' results showed a significant negative decreasing trend, as well as two (2) stations, found no statistically significant monotonic trend change presented in (Figure 4.5).

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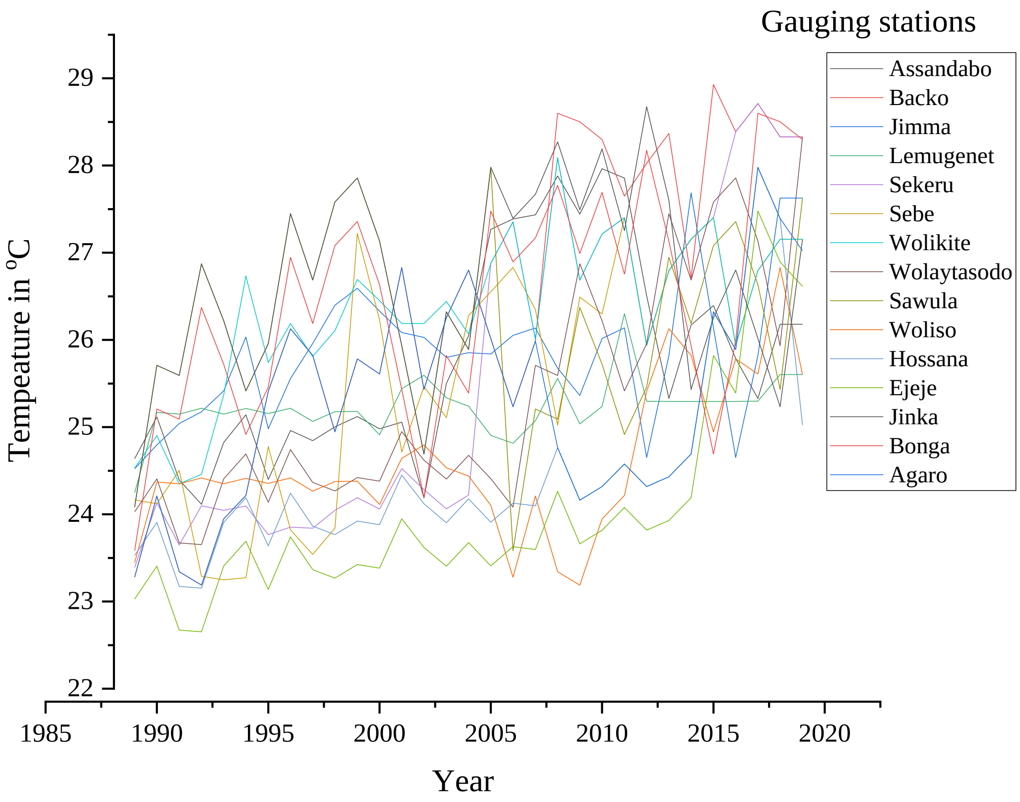

Figure 4.5: Annual Average Temperature Changes in Omo-Gibe River Basin (1989-2019). (Author's Construct, 2022).

The baseline seasonal average temperature trend test result showed the eleven (11) meteorological gauging stations a significant positive increasing trend, two (2) meteorological gauging stations' results showed a significant negative decreasing trend, as well as two (2) stations, found no statistically monotonic trend change in seasonal temperature as shown in (Figure 4.6).

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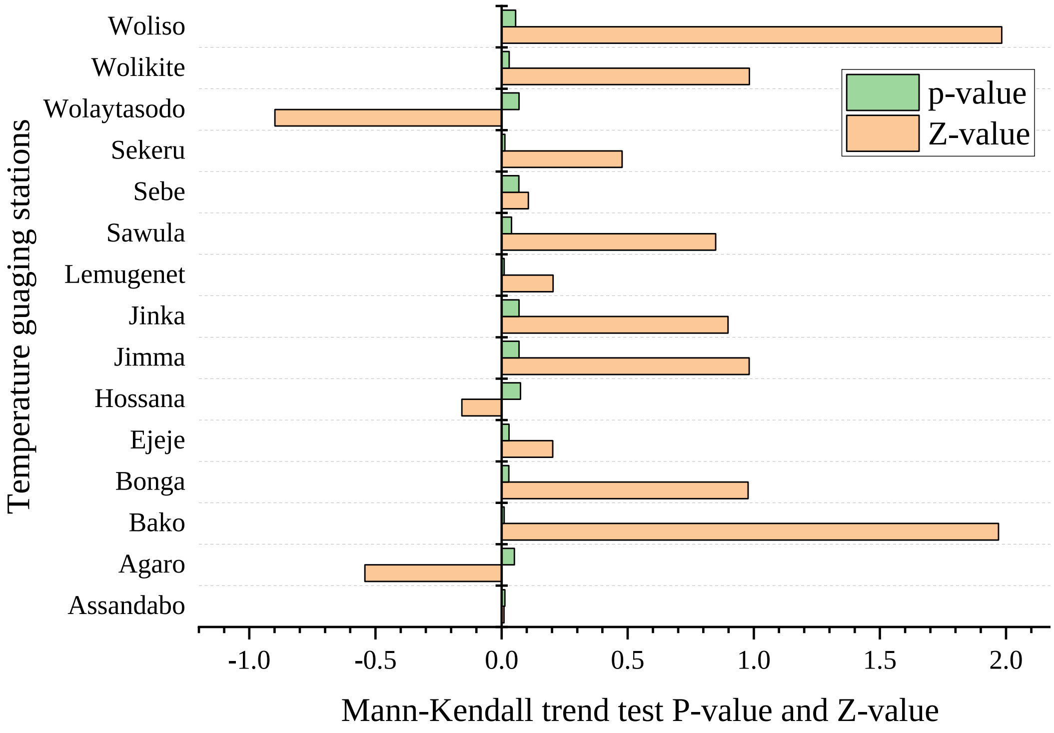

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Figure 4.6: Changes in Seasonal Average Temperature in Omo-Gibe River Basin During (1987-2019). (Author's Construct, 2022).

4.2.2 Evaluation of Projected Annual and Seasonal Temperature for Statistically Significant Change and Trend Detection

Temperature trends with statistical significance were found for the following 83 years (2017–2100) after an analysis of yearly and seasonal temperature variations. The minimum and maximum temperatures in the basin were projected using the RCP 8.5 and RCP 4.5 emission scenarios for three (3) future periods: short-term (2017-2044), medium-term (2045-2072), and long-term (2073-2100). Trend analyses revealed that the emission scenarios RCP8.5 and RCP84.5 both predicted a significant increase in the average annual temperature. The results of the trend test analysis are shown in (Figures 4.7 and 4.8), which show that the annual minimum and maximum temperatures in the river basin area show increasing trends for the three (3) time periods under the RCP4.5 and RCP8.5 emission scenarios.

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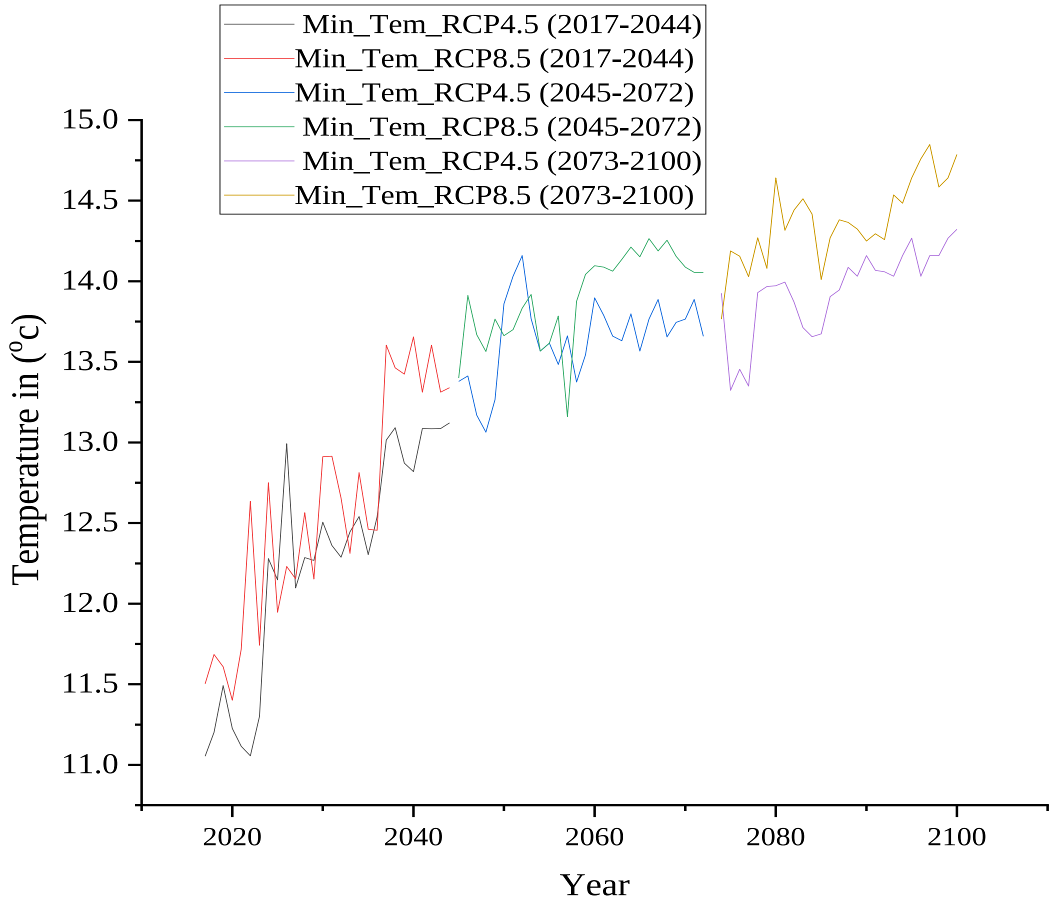

Figure 4.7: Projected Change in Annual Minimum Temperature under RCP4.5 and RCP8.5 Emission Scenarios (2017-2100). (Author's Construct, 2022).

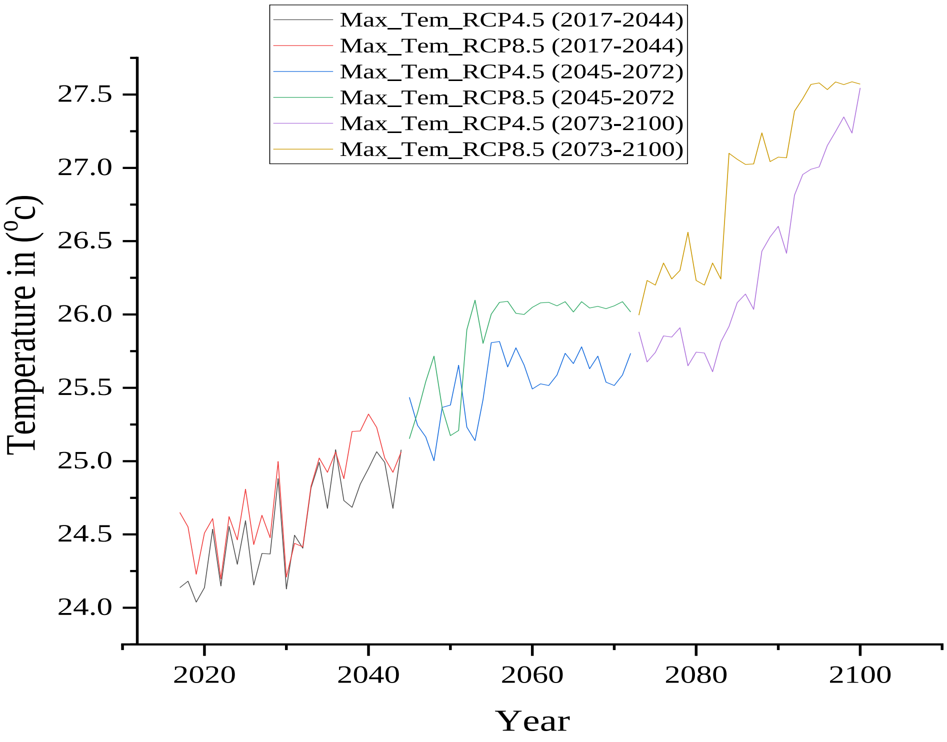

Figure 4.8: Projected Change in Annual Maximum Temperature under RCP4.5 and RCP8.5 Emission Scenarios (2017-2100). (Author's Construct, 2022).

The projected average results from the fifteen RCMs indicate that temperatures would increase over time in comparison to the base period under the RCP8.5 and RCP 4.5 emission scenarios. Under emission scenarios, RCP8.5 and RCP4.5, the mean annual temperature in the depicted river basin (Figure 4.9) increased throughout the three (3) future periods relative to the reference period.

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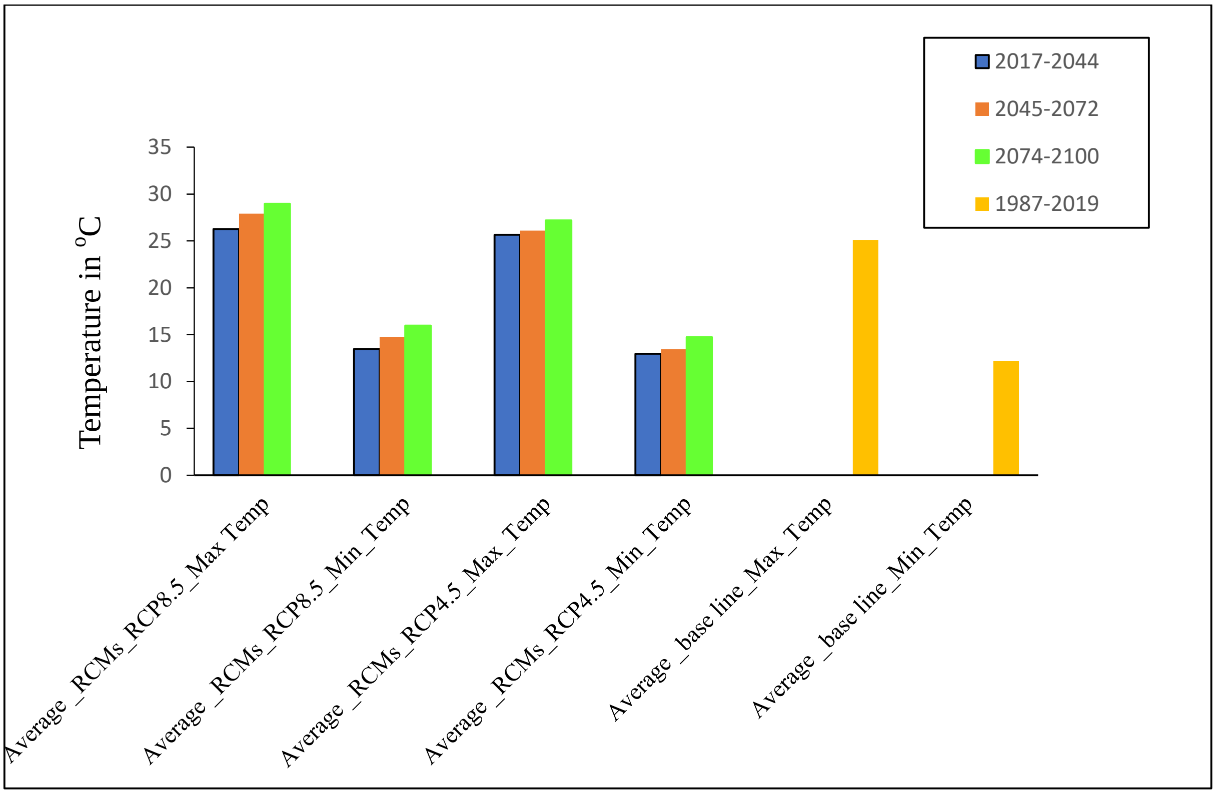

Figure 4.9: Changes in Annual Average Maximum and Minimum Temperatures Projected in the RCP 4.5 and RCP 8.5 Emissions Scenarios Over the Period (2017-2100) and Observed over the Period (1987-2019). (Author's Construct, 2022).

Based on analysis using the RCP4.5 and RCP8.5 emission scenarios, it is expected that the river basin will experience a significant increase in temperature throughout the three (3) future periods shown in (Figure 4.10).

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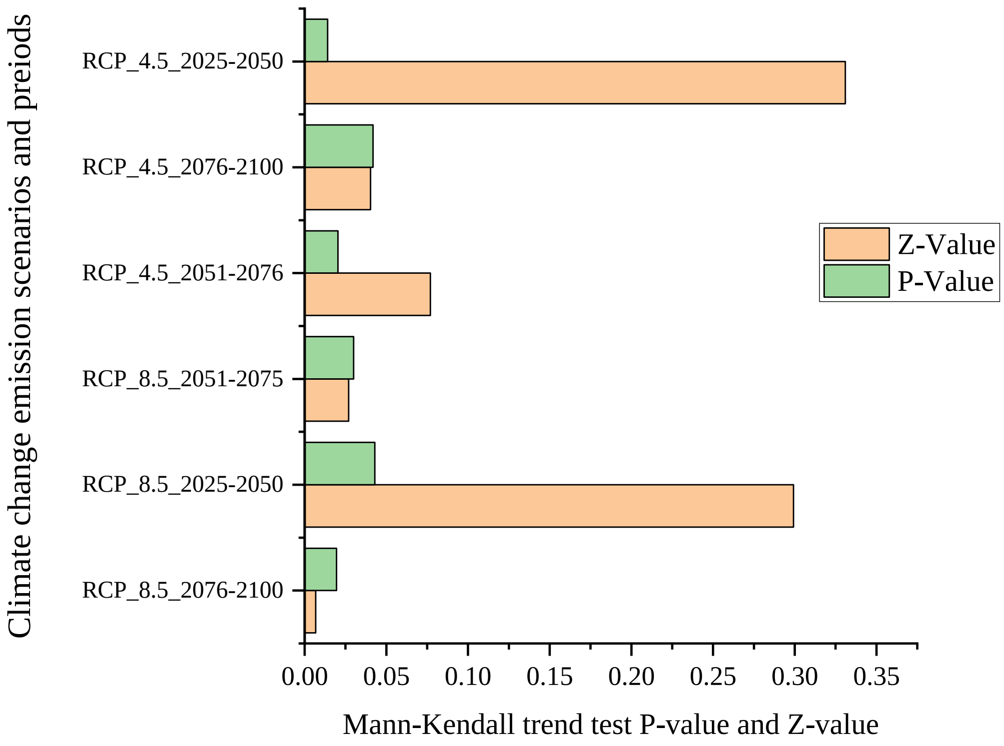

Figure 4. 10: Change in Projected Average Seasonal Temperature under RCP 4.5 and RCP 8.5 Emission Scenarios Over the Period (2017-2100). (Author's Construct, 2022).

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Under the emission scenarios RCP 8.5 and RCP 4.5 for three (3) future periods, the anticipated monthly minimum and maximum temperatures as well as river basin temperatures have been evaluated. According to the RCP8.5 and RCP4.5 emission scenarios, it is anticipated that the monthly change in maximum (Figure 4.11) and minimum (Figure 4.12) temperatures will result in a significant increase over the following three (3) future periods in comparison to the base period.

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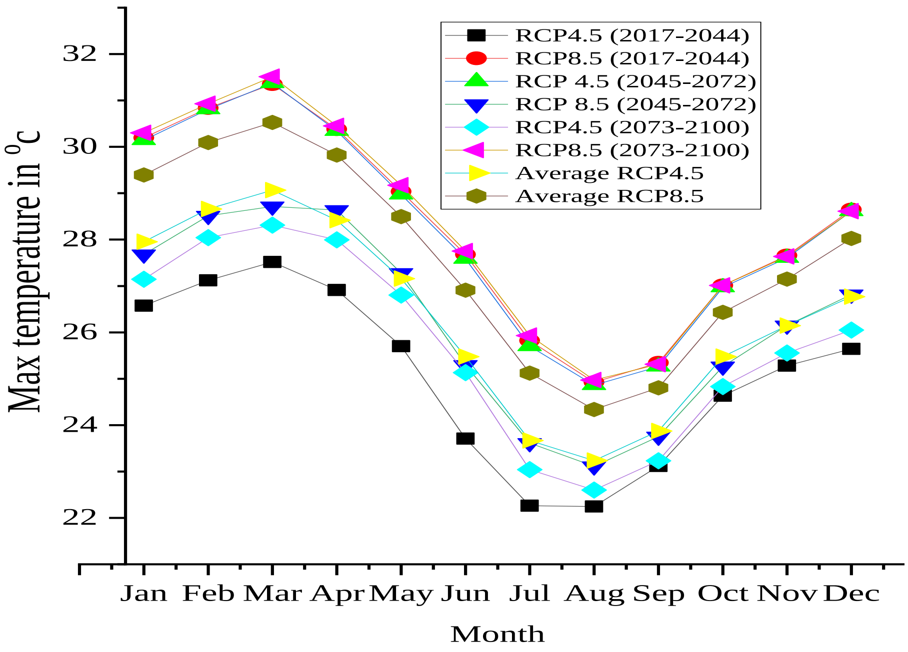

Figure 4.11: Projected Changes in Monthly Maximum Temperature under RCP 4.5 and RCP 8.5 Emissions Scenarios (2017-2100). (Author's Construct, 2022).

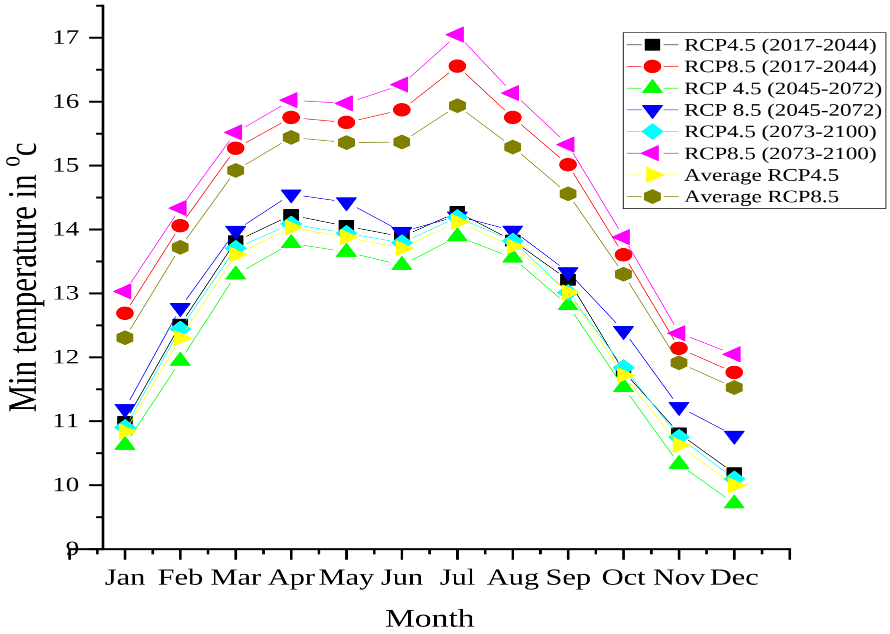

Figure 4.12: Projected Changes in Monthly Minimum Temperature under RCP 4.5 and RCP 8.5 Emissions Scenarios (2017-2100. (Author's Construct, 2022).

4.2.3 Evaluation of Observed Annual and Seasonal Precipitation for Statistically Significant Change and Trend Detection

Statistically significant, detect trends and projected change of baseline period (1987-2019) over 32-years and future periods 83-years annual and seasonal precipitation change were evaluated and compared with the Baseline period. The baseline period of fifteen rainfall gauging stations of the Omo-Gibe Basin precipitation trend change was analyzed. Annual time series precipitation data patterns change, analyzed results showed a significantly decreasing trend at the eleven (11) meteorological gauging stations in the basin. Trend detection test, on the other hand, found no statistically significant monotonic trend change in annual precipitation at the four (4) meteorological gauging stations are indicated (Figure 4.13).

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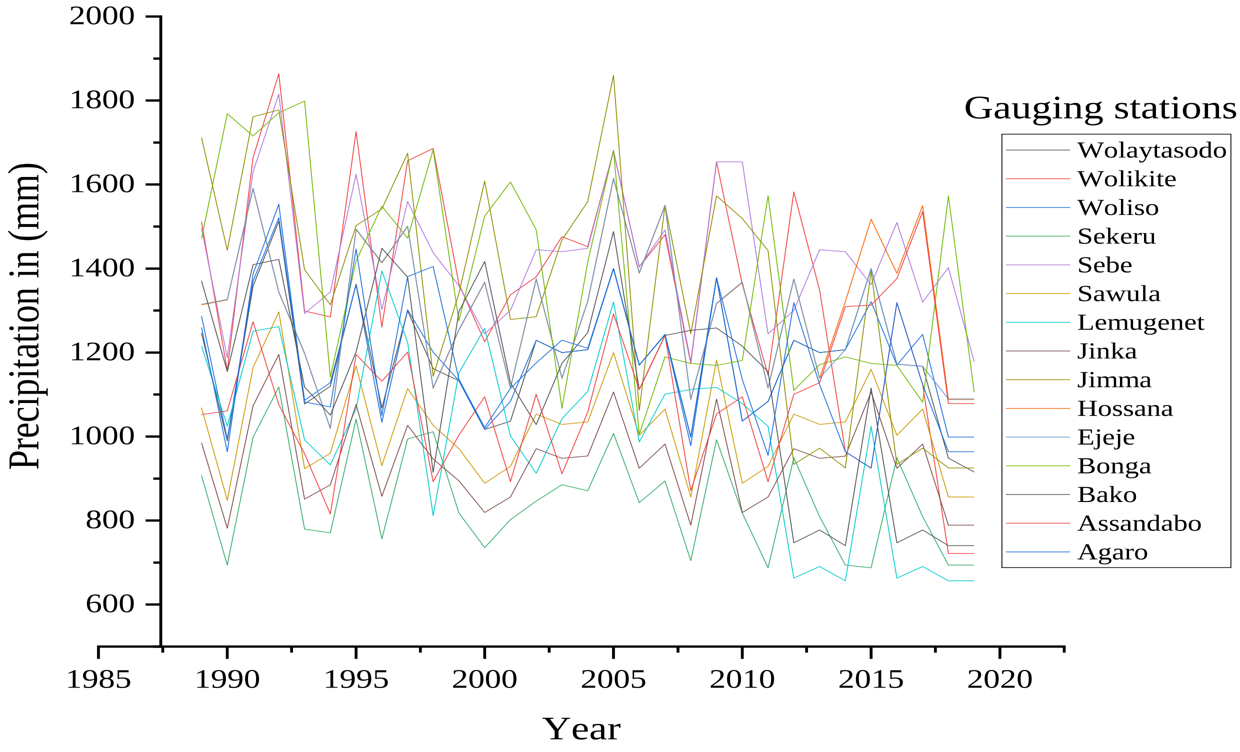

Figure 4.13: Observed Annual Precipitation Changes in Omo-Gibe River Basin Over the Period (1989- 2019). (Author's Construct, 2022).

Using a reference period of Fifteen (15) precipitation measurement stations, the seasonal trend change in precipitation investigation was conducted in the Omo-Gibe River Basin. The Eleven (11) meteorological stations' data revealed a pronounced downward trend, pointing to a shift in the seasonal precipitation distribution patterns. But none of the Four (4) meteorological stations listed in the figure's trend detection test results (Figure 4.14), found statistically significant monotonic trends in the seasonal precipitation distribution.

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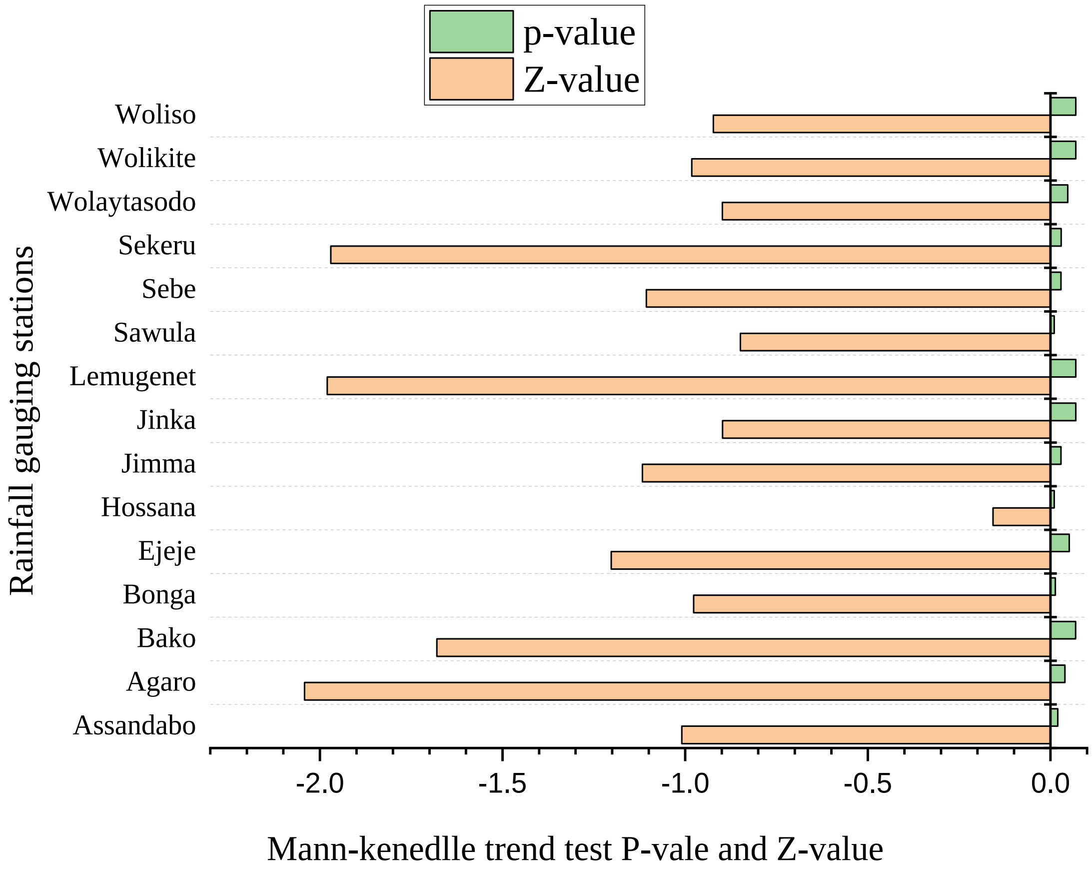

Figure 4.14: Observed Seasonal Precipitation Change in Omo-Gibe River Basin Over the Period (1987- 2019). (Author's Construct, 2022).

4.2.4 Evaluation of Projected Annual and Seasonal Precipitation for Statistically Significant Change and Trend Detection

Statistically significant trends for the years (2017-2100) over 83 years were discovered after evaluating the change in precipitation on an annual and seasonal basis. For three (3) upcoming study periods with trend changes, the annual precipitation amounts were projected using the RCP4.5 and RCP8.5 emission scenarios. Based on the results of the trend tests for the RCP4.5 and RCP8.5 emission scenarios, a significant decrease in annual precipitation amounts was predicted.

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The predicted precipitation for the Omo-Gibe River Basin was assessed for three (3) future periods: the short term (2017-2044), the medium term (2045-2072), and the long term (2073-2100) when compared to the reference time (Figure 4.15). The expected changes in annual precipitation over the ensuing three (3) future periods were evaluated using the average results of the fifteen (15) RCMs models under the RCP4.5 and RCP8.5 climate change scenarios. Predicted precipitation is expected to generally trend downward in comparison to the reference period, according to the average results of the fifteen (15) RCMs models (Table 4.2 and Figure 4. 15).

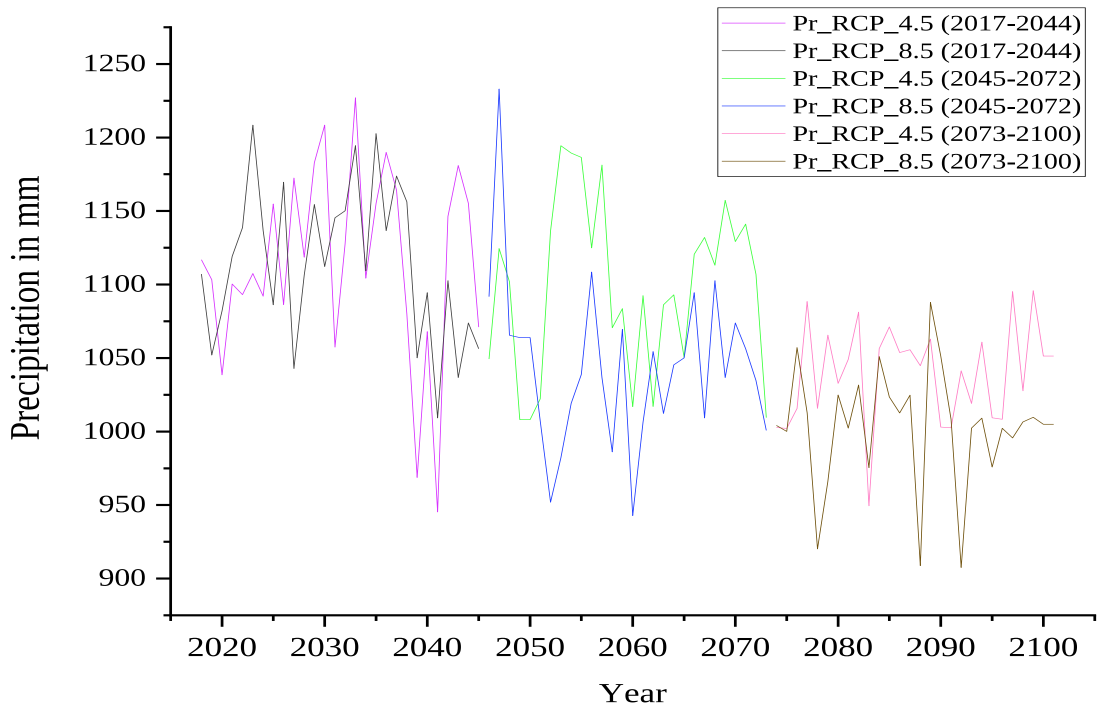

Figure 4.15: Projected Changes in Annual Precipitation under RCP 4.5 and RCP 8.5 Emissions Scenarios (2017-2100). (Author's Construct, 2022).

The trend test revealed that over three (3) future study periods, the predicted seasonal precipitation distribution under the RCP8.5 and RCP4.5 emission scenarios showed a decreasing trend. On the

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other hand, this indicates that the river basin area (June to August) will experience the peak summer rainy season as well as the erratic spring rainy season under the evaluated emission scenarios for (Figure 4.16) depicts the emission scenarios for RCP8.5 and RCP4.5.

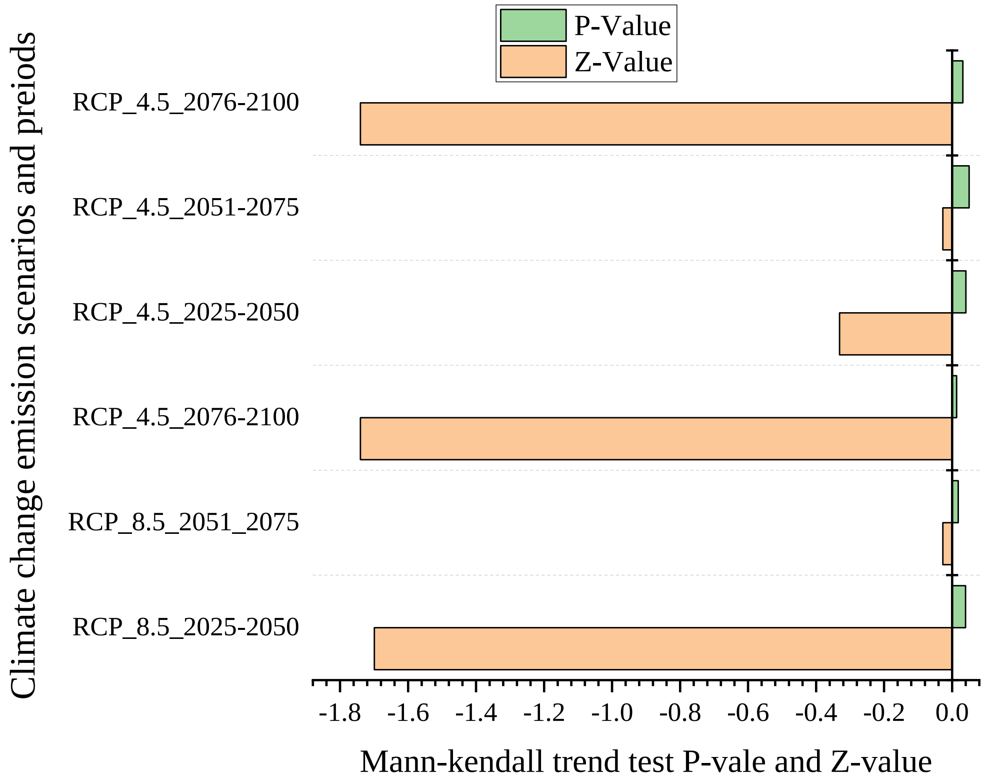

Figure 4.16: Projected Seasonal Precipitation Change under RCP_4.5 and RCP_8.5 Emission Scenarios (2017-2100). (Author's Construct, 2022).

The predicted changes in monthly precipitation and monthly average precipitation over the ensuing three (3) future periods were evaluated. The average results of the fifteen (15) RCMs were used to calculate the projected monthly and monthly mean precipitation. The average results of the fifteen (15) RCMs models in the following three (3) periods will see a decline under the RCP8.5 and RCP4.5 emission scenarios (Table 4.2 and Figure 4.17).

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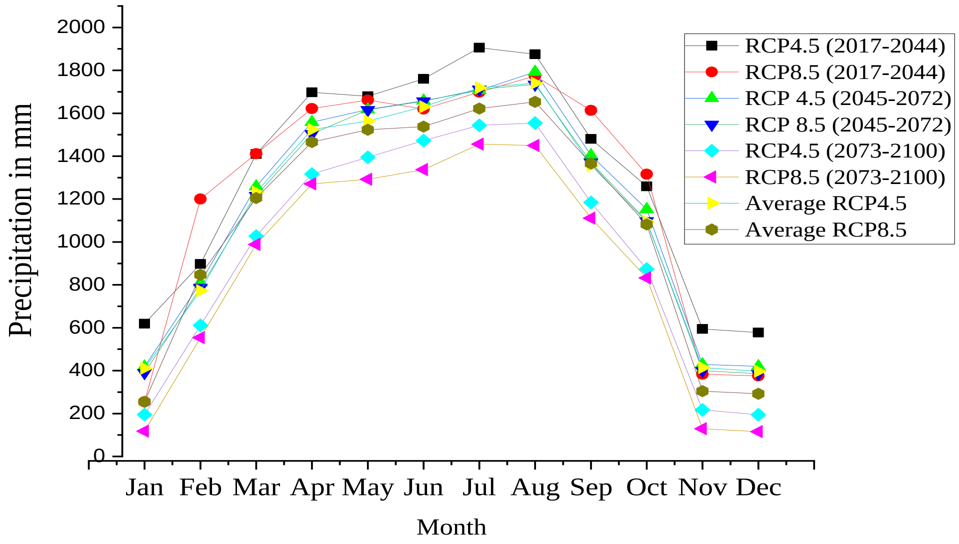

Figure 4.17: Projected Changes in Monthly Mean Precipitation under RCP 4.5 and RCP 8.5 Emissions Scenarios (2017-2100). (Author's Construct, 2022).

Under the emission scenarios RCP 8.5 and RCP 4.5, the predicted changes in precipitation in terms of annual amount and seasonal distribution were assessed and contrasted to the basin reference period for three (3) future periods (Table 4.4). Predicted that, compared to the baseline period, the annual amount and seasonal distribution of the two (2) rainy seasons summer from June to August and spring from March to May will decrease in the future.

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Table 4.3: Annual and Seasonal Precipitation Projected and Percentage Change.
Source: (Author's Construct, 2022).

Years	Baseline and projected total annual precipitation in (mm)	Projected change average annual precipitation in (mm)	Projected change average precipitation during the main rainy season in (mm)	Percentage change projected average precipitation in the main rainy season (%)	Projected change average precipitation during the erratic rainy season in (mm)	Percentage change projected average precipitation in the erratic rainy season (%)
PR_ Baseline period 1989-2019	14400.70	-	-	-	-	-
Pr_RCP_85_ 2025-2050	13058.04	1088.17	614.19	10.13	473.99	12.08
Pr_RCP_85_ 2051-2075	12017.30	1001.44	612.49	11.17	388.95	13.98
Pr_RCP_85_ 2076-2100	10791.60	982.63	603.08	13.18	379.55	14.54
Pr_RCP_45_ 2025-2050	13060.08	1090.01	614.27	10.12	475.74	11.42
Pr_RCP_45_ 2051-2075	12089.50	1007.46	615.50	11.17	391.96	12.79
Pr_RCP_45_ 2076-2100	11869.03	999.09	606.31	12.72	392.78	13.55

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4.2.5 Evaluation of Observed Annual and Seasonal Streamflow for Statistically Significant Change and Trend Detection

The variation in annual and seasonal streamflow baselines (1987-2019) over 30 years was statistically analyzed, and statistically significant decreasing trends were found. For the annual trend of the Omo-Gibe River basin, examined variations in streamflow magnitude over the reference period. Figure 4.18 displays the data analysis findings, which show a statistically significant downward trend and the reference period for annual streamflow change. Additionally, the trend test analysis revealed that annual and seasonal streamflow will decline over time (Table 4.5), which is consistent with the under two (2) RCP 8.5 and RCP 4.5 emissions scenarios.

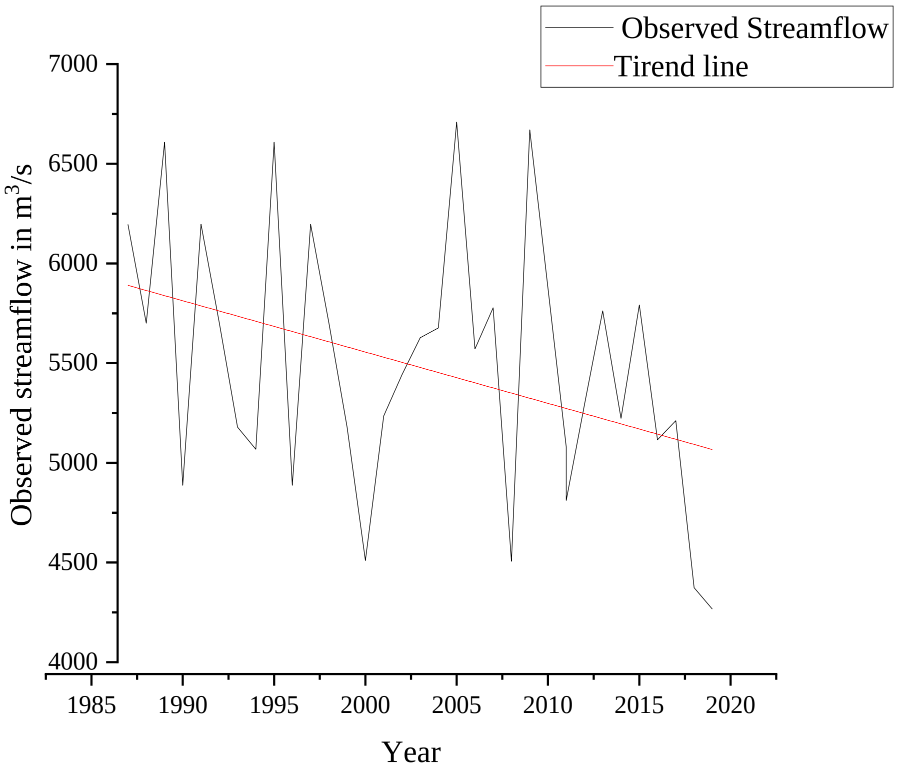

Figure 4.18: Historical Annual Streamflow Change in the Baseline Period from (1987–2019). (Author's Construct, 2022)

4.2.6 Evaluation of Projected Annual and Seasonal Streamflow for Statistically Significant Change and Trend Detection.

Forecasted annual and seasonal streamflow variations reveal trends that are statistically significant over 83 years (2017–2100). Omo-Gibe basin streamflow was studied using the subsequent three (3) periods. In (Figure 4.19), future periods of streamflow change for the three (3) periods of annual streamflow change are discussed, along with assessment results that show a statistically significant downward trend. Additionally, the trend test analysis and assessments show that seasonal streamflow has decreased over the study period under the two (2) RCP 4.5 and RCP 8.5 emissions scenarios (Figure 4. 20).

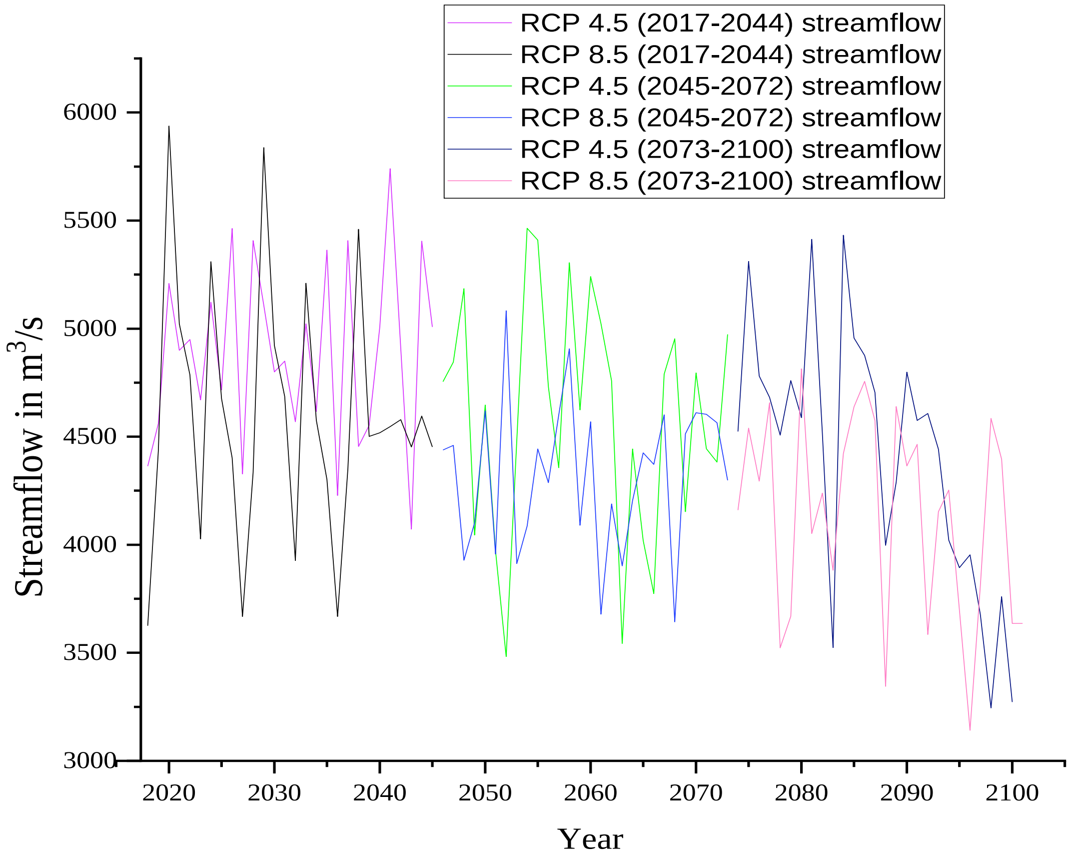

Figure 4.19: Projected Changes in Annual Streamflow under RCP 4.5 and RCP 8.5 Emissions Scenarios (2017-2100). (Author's Construct, 2022).

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The outcomes of this study show decreasing trends over the short-, medium-, and long-term (2017-2044, 2045-2072, and 2073-2100) in (Figures 4.19, 4.20, and 4.21), which represent the estimated and projected change in average annual streamflow over three-time scales. Overall, the project's findings showed that under the two (2) RCP8.5 and RCP4.5 emission scenarios, annual and seasonal streamflow should be lower than during the historical period (Figure 4.18).

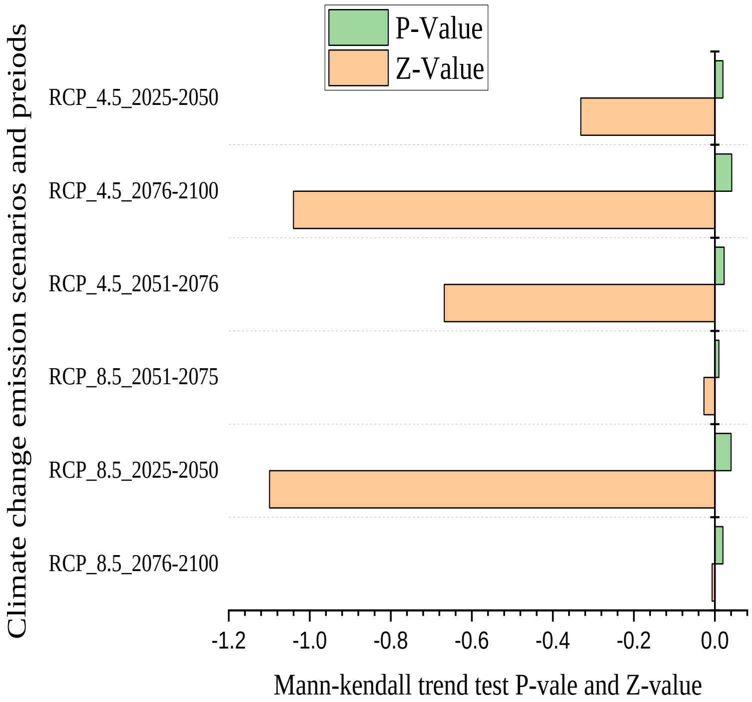

Figure 4.20: Change in Predicted Seasonal Streamflow under RCP4.5 and RCP8.5 Emission Scenarios (2017-2100) (Author's Construct, 2022).

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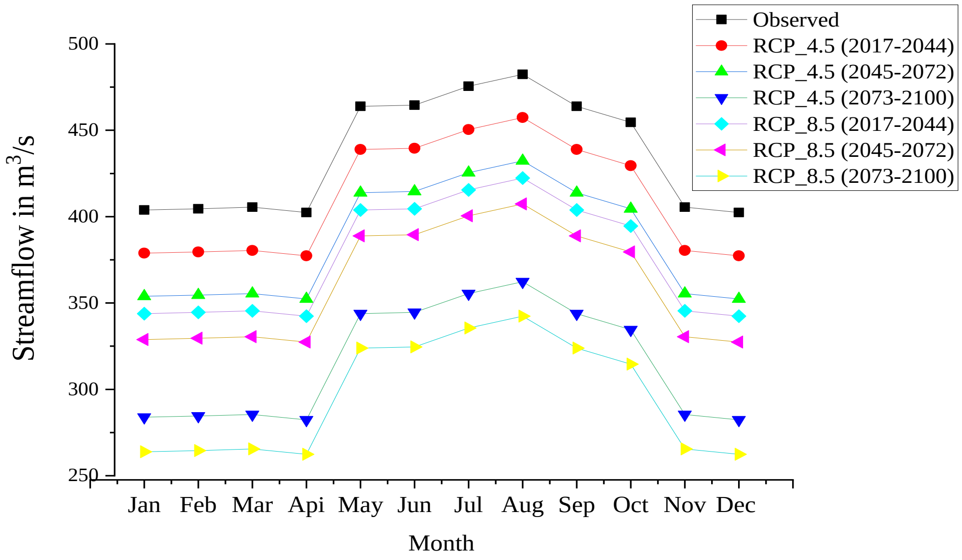

Figure 4.21: Projected Changes in Monthly Streamflow under RCP 4.5 and RCP 8.5 Emissions Scenarios During (2017-2100). (Author's Construct, 2022

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For three (3) future periods, as shown in (Table 4.5), the estimated and projected magnitude of the seasonal and annual changes in streamflow were evaluated using a variety of techniques. The mean monthly streamflow during the dry season, mean monthly streamflow during the rainy season, and the annual total streamflow were all compared to the baseline period along with the projected streamflow magnitudes and percentage changes. According to predictions made under the RCP4.5 and RCP8.5 emission scenarios, as shown in (Table 4.5), the Omo-Gibe River Basin's annual and seasonal streamflow magnitude will decrease relative to the reference era for all three (3) of the future study periods (Table 4.5).

Table 4.4: Predicted Changes in Annual and Seasonal Streamflow under RCP 4.5 and RCP 8.5 (2017-2100).

Years	Simulated total annual streamflow (m^3/s)	Monthly mean streamflow (m^3/s)	Annual mean streamflow percentage change %	The dry season means monthly streamflow (m^3/s)	Dry season mean monthly streamflow percentage change %	Rainy season monthly mean streamflow (m^3/s)	Rainy season monthly mean streamflow percentage change %
Baseline_ 1991-2019	5142.6	428.56	-	204.26	-	224.3	-
RCP_85_ 2025-2050	4838.4	400.4	7.02	191.6	4.02	211.6	3.00
RCP_85_ 2051-2075	4802.4	390.6	8.78	190.1	4.54	210.1	3.23
RCP_85_ 2076-2100	4837.2	370.8	10.99	191.55	6.22	211.6	4.77
RCP_45_ 2025-2050	4940.4	410.7	10.98	195.85	6.52	215.9	4.46
RCP_45_ 2051-2075	4929.6	400.8	11.93	195.4	7.20	215.4	4.73
RCP_45_ 2076-2100	4903.2	380.6	12.88	194.3	8.00	214.3	4.88

Source: (Author's Construct, 2022)

4.3 Development of Socio-Economic and Climate Scenarios for Future Water Demand and Allocation

WEAP permits the use of a variety of scenarios, including socio-economic, current, and referenced scenarios. This makes it possible to simulate the present and the future, provide answers to numerous "what if" questions, and make comparisons to the current situation (Sieber and Purkey, 2015). Current account scenarios depict the water supply system's current state and include supply and demand information for the study's first year (current account). Every scenario starts in the current year because it is also the first year of the baseline scenario and all other scenarios. The WEAP scenarios make many assumptions regarding upcoming policy changes, economic growth, and other supply and demand-related issues. It is possible to assess the consequences of climate change and the water supply by developing and contrasting scenarios. Each scenario begins with the year in which the current account data were gathered. Any variable that can change over time, such as assumptions about socioeconomic conditions and climate change, can be included in WEAP scenarios.

The reference scenario and current accounts (using 2017 as the starting year) are used to run model simulations. The current accounts for the foreseeable future (starting in 2017) and seven (7) water demand, socioeconomic, and two (2) climatic scenarios were developed. These scenarios included the climate change scenarios RCP4.5 and RCP8.5 as well as population expansion, an increase in irrigated land, an increase in hydropower plants, and an increase in livestock. The outcomes of baseline simulations were applied to calculate the future relative change from the baseline period.

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The input data for socio-economic variables, water supply, and water demand were used to create these WEAP model scenarios. The current water supply scenarios are the current scenarios based on the data that is currently available. Irrigation, domestic, hydropower, industrial and commercial, livestock, recreational, and institutional businesses in the river basin are the main determining factors in the water demand and consumption scenarios. The scenarios created were the current account base scenario from 2017, the scenario of the current population growth rate, the scenario of the environmental flow, the scenario of the current irrigation potential, changes in economic development patterns, the scenario of the irrigation scheme, the scenario of the projected population growth rate, the medium or stabile climate change scenario RCP 4.5 scenarios, and the high or worst-case climate change scenario RCP 8.5.

4.4 Developing Assumptions for Future Water Availability and Allocation Related to Current Surface Water Consumption

Important water demand and consumption within the basin have been identified and quantified to evaluate present and future water needs to the status of water availability. To analyze the future water availability scenario, which predicts future water use; availability, and demand, assumptions had to be made. Sectors with the highest priority for meeting the water demand include irrigation, domestic, hydropower, industrial and commercial, livestock, recreational, and institutional, and business. Due to climate change and socioeconomic development, the sector's demand for and consumption of water will impact the streamflow of the sub-river basin in the future, which will then impact water availability. The basis for these development hypotheses was the annual water consumption of million cubic meters (MCM), which was calculated by combining demand site data from competing water uses. The WEAP model was used to estimate

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water demand and allocation in the current and future under various scenarios using the amount of water as input data. Using information from various sources, the annual water use for the Omo-Gibe River basin has been calculated and estimated (Table 3.3).

Domestic consumption can be determined based on the population utilizing the water networks and the particular water requirements. For all sectors, it was assumed that the annual variation in water consumption and the environmental flow would remain at 60 m^3/s throughout the year. The highest anticipated demand for irrigation water is in the Lower Omo Basin. Three (3) sub-basins (1, 2, and 3) comprise the irrigated land in this basin and are located downstream from the irrigation projects in Kuraz. Calculating the annual consumption rate of water demand at the basin, the Omo-Gibe River basin is informed by information from many sources for all sectors (annual water) (Table 3.3). Irrigation water loss from the system is anticipated due to the significant evapotranspiration losses (Table 3.3). To achieve the right groundwater balance, an alternative system is needed. In addition to using external groundwater modeling, the strategy would connect irrigation regions to aquifers in WEAP. Due to a lack of information on the groundwater in each sub-basin, this strategy would, however, go beyond the parameters of the study and require more time and resources.

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4.5 Estimation of Unmet Water Demands under Different Scenarios

There are five (5) dams in the river basin. Gibe II does not serve as a reservoir but there are two (2) existing reservoirs (Gilgel-Gibe I and Gibe III). The WEAP model does not contain one that is under construction and one that is planned. Gibe II does not have a dam, but it collects water from Gilgel Gibe I after passing through. Two (2) existing reservoirs have stored water for hydropower (Gilgel-Gibe I and Gibe III). Under-construction and planned hydropower projects are normally

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set to be inactive in current accounts, and they are assigned various start-up years in the scenarios that incorporate them. The following socio-economic, climatic, and future water demand scenarios were utilized in the study:

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Baseline scenario: The baseline scenario uses 2017 as the year, takes the current account into account, and provides the system's actual water demand and supply. Based on current water supply and demand projections for 2017, the current water use was calculated.

1. Reference: refers to the current account of the business-as-usual scenario; this is the baseline scenario that makes use of all real-time data and represents the current actual situation that is modeled and projected under the current year (2017) situations and conditions, taking into consideration assumptions of population growth rate, land use, and unit consumption. About 14,580,516 people live in the rural and urban areas of the Omo-Gibe River basin. Ethiopian Electric Power (EEP) continues to release a continuous flow of basin streamflow is 60 m^3/s from the Gibe III hydroelectric project, exceeding the minimum dry-season flow requirement of 25 m^3/s magnitudes. When determining the water demand, ecosystem water use has not been taken into account. The reference scenario had seven (7) types of sectoral demand irrigation, domestic (including, consumption of rural and urban population), hydropower generation, industrial and commercial (including, manufacturing, processing, washing, and cooling; mining, thermal power generation), livestock animal husbandry (including, cattle, sheep, goats, and horses) and recreational and institutions, and businesses based on annual water use, the demand site data statistics were established and were estimated for the basin.

Figures 4.22 and 4.23 show the annual water demand use for 2017 (current account) for the irrigation, domestic, hydropower, industrial and commercial, livestock, recreational and institutions, and business sectors, with total water demand of 5,443.54 million cubic meters (Mm^3). Irrigation is the largest sector basin, with the highest annual water demand of 5,032 Mm^3 (92.44 %) in the current year, followed by domestic demand of 258.3 Mm^3 (4.75 %), hydropower 91 Mm^3 (1.67 %) industrial and commercial 28.9 Mm^3 (0.53 %), livestock 28 Mm^3 (0.51 %), recreational 4.1 Mm^3 (0.08 %) and institutions and businesses 1.23 Mm^3 (0.02 %).

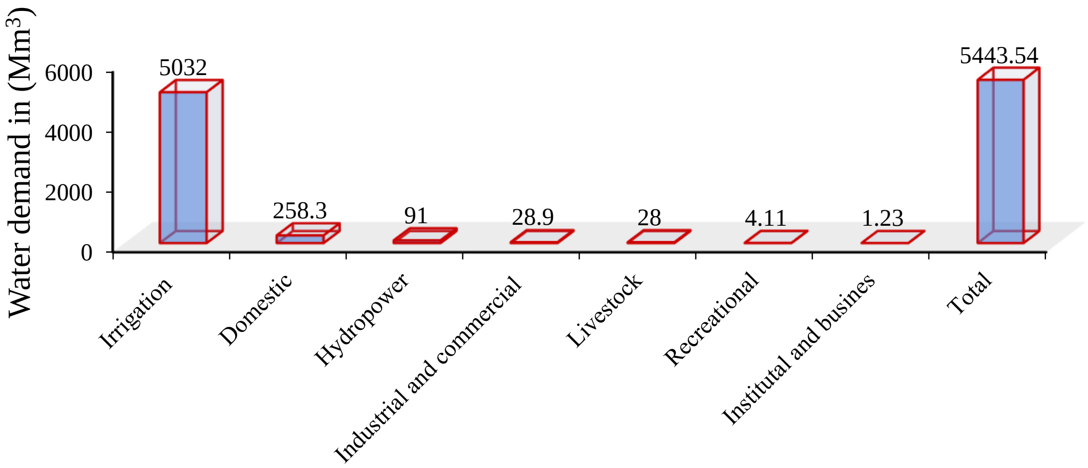

Figure 4.22: Total Water Demand for the Baseline Period (2017) Scenario in the Omo-Gibe River Basin. (Author's Construct, 2022).

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This socio-economic reference period-based scenario includes the current account data in the entire model and projects the outputs (2017–2100). It helps to understand the situation during the study periods of the basin (Sieber and Purkey, 2013). The water demand was increasing moderately. WEAP simulation of the projected results, in the scenario, the biggest water demand was irrigation, domestic, hydropower generation, industrial and commercial, livestock, Institutions and businesses, and recreational respectively.

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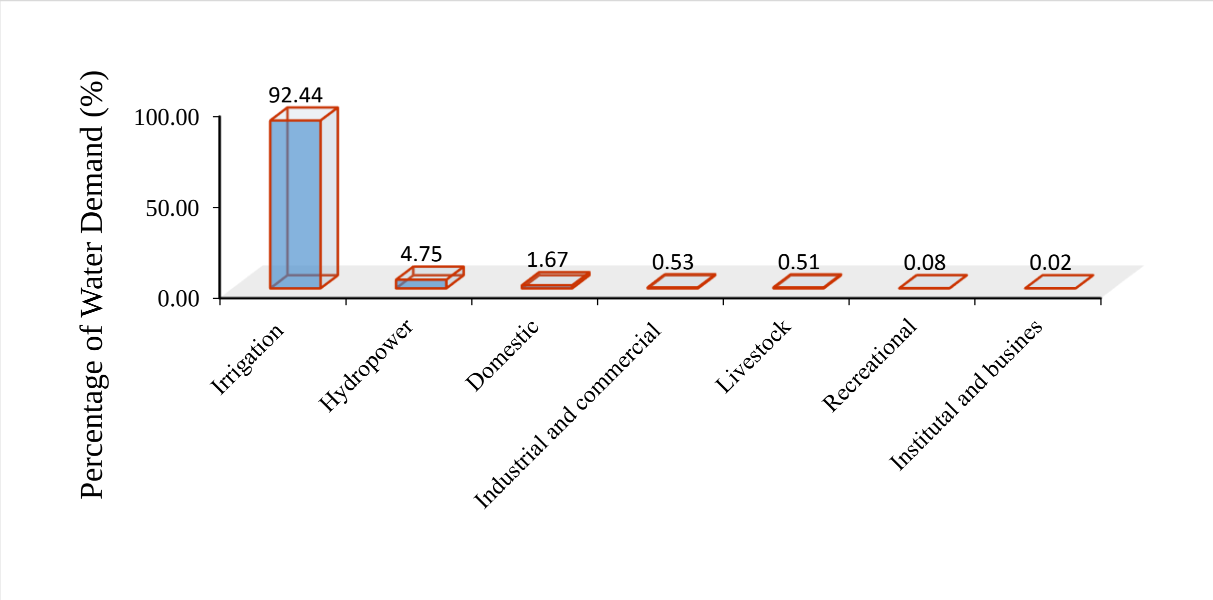

Figure 4.23: Total Water Demand Percentage for the Baseline (2017) Scenario in the Omo-Gibe River Basin. (Author's Construct, 2022).

4.6 Unmet Water Demand in the River Basin due to Increasing Demands

1. Irrigation area expansion: According to the master plan and the strategic report of the river basin project, small, medium, and ample irrigation areas are 208,655 hectares. The current irrigated area of 208,655 hectares is expected to reach 417,310 ha, an increase of 100 % in irrigable land.

As a proportion of overall unmet demand, water scarcity is estimated at 31.10 %. This situation will have a more significant impact on the irrigation business than on other sectors.

Domestic, livestock, industrial, and commercial sectors will be affected by 29.5 %, 26.4 %, and 24.5 %, respectively, while recreational, institutional, and commercial sectors will be impacted by 9.9 % and 9.7 %, respectively.

2. Population growth increase: Based on the master plan and strategic report, current water use in urban areas is expected to be between 10 and 13 % and 5 % in rural areas. The current population of the river basin is 14,580,516 compared to 2017, based on projections from the 2007 CSA Census, with a population growth rate of 2.4 %. All other industries are expected to experience slow growth, which means that demand in 2100 will be similar to the current demand. As a result, water availability will fully meet household water demand in the baseline scenario (based on a previous population growth rate of 2.4 %). If the scenario, on the other hand, all other sectors are expected to grow at a maximum rate, a population growth rate of 3.0 - 3.5 % by 2100 according to this scenario, demand will grow in 2100. The total expected water demand within the basin will not be met at 21.0 %. Hydroelectricity, industrial and commercial activities, irrigation, institutions and businesses, and recreational activities are only some of the industries that will be affected by population growth. Irrigation, hydroelectricity, industry and commerce, institutes and businesses, and recreation will all have future unmet demands of 25.6 %, 23.65 %, 19.20 %, 15.31 %, 12.10 %, and 4.19 %, respectively.

3. Hydropower energy production (generation) increases. Currently, two reservoirs exist within the basin. The scenario describes what could be projected if the number of reservoirs is increased by 50 % and hydroelectric generation is favored for full capacity by 2100. The present

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flow rate of the turbine is 15,540 m^3/s and its maximum capacity is 91 m^3 s1. As a result, 20.4 % of the total water demand in the basin will be unmet (Figure 4.24). Hydropower generation will be most affected by the overall shortage, with an unmet demand of 28.20 %, followed by irrigation at 26.6 %, livestock at 24.2 %, and industrial and commercial at 22 %.

4. Livestock population growth: To forecast future livestock growth and water consumption by 2100, a cattle population growth rate of 2.6 % to 4 % was adopted. This scenario has the fourth most incredible impact on water use relative to all other situations. There will be an annual water shortage of 21.3 %, depending on the animal population growth scenario. In this case, the total unsatisfied demand for irrigation, industrial and commercial, hydroelectricity, and households was 28.33 %, 26.30 %, 25.27 %, and 20.13 % respectively.

5. Industrial and commercial sectors increase. With a 50 % increase in the industrial and commercial sectors, the model projects a water shortage of 3.3 % per year by 2100. For irrigation, hydropower, livestock, institutions, businesses, and recreation, water shortages are projected to be 29.6 %, 28.5 %, 24 %, and 5.35 %, respectively. In this scenario, the impact on institutions, businesses, and recreational sectors will all be negligible.

6. Institutions and Businesses and Recreational Activities Increase: Compared with all other sectors and scenarios, these have the lowest impact on water consumers. With an increase of 50 % under the institutional and commercial, and recreational scenarios, an annual water shortage of 1.5 % and 1.4 %, respectively, is forecasted. Hydropower, irrigation, domestic, livestock, industrial, and commercial demand were all hit hard; with shortages of 27.11 %, 25.89 %, 18.99 %, 15.66 %, and 12.44 %, respectively.

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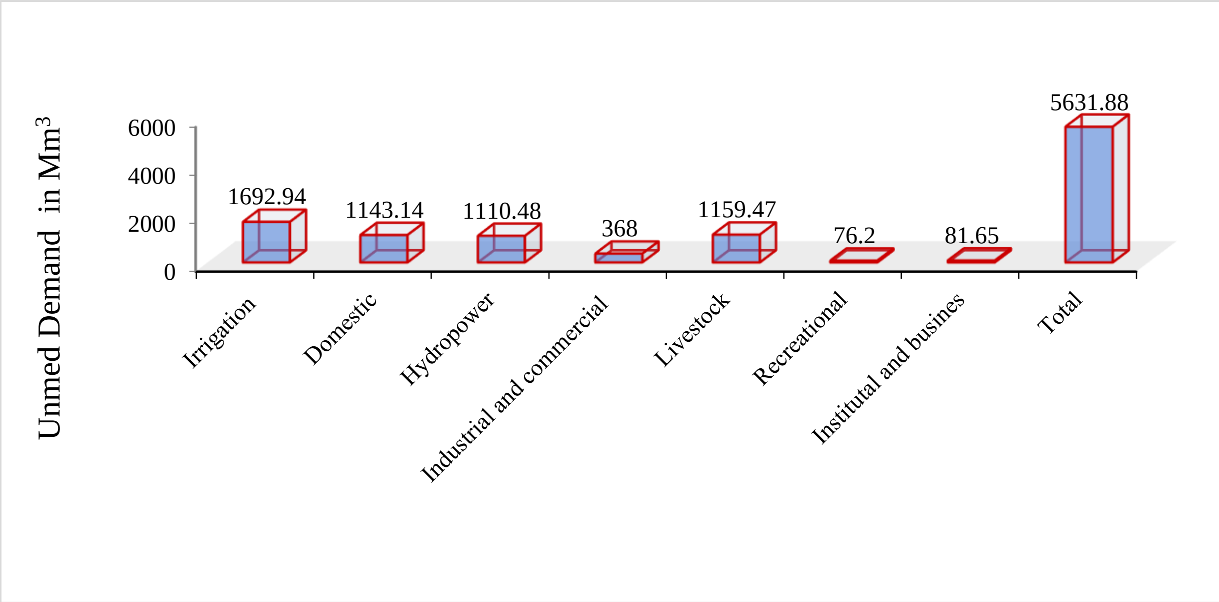

Figure 4.24: Unmet Water Demand in the River Basin due to Increasing Demand in all Sectors. (Author's Construct, 2022).

Water demand in the study area is expected to increase significantly over the upcoming years. This reflects development in all areas of the economy, growing demand, increased water use, and shifting river climate. According to (Table 4.5 and Table 4.6), this is due to an increase in demand across all industries, increased water use, and a changing climate in the river basin.

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Table 4.5: Reference Scenario Projected Water Demand (million cubic meters, Mm^3) for each Sector under RCP 4.5 from (2017 to 2100).

Year	Irrigation	Domestic	Hydropower	Industrial and Commercial	Livestock	Recreational	Institutional and Businesses	Total Water Demand
2017	5032.00	258.30	91.00	28.90	28.00	4.11	1.23	5443.54
2024	5273.85	421.61	249.64	31.22	35.31	4.59	12.89	6029.11
2031	5515.70	584.91	408.28	33.54	42.62	5.07	24.56	6614.67
2038	5757.55	748.22	566.92	35.86	49.93	5.55	36.22	7200.24
2045	5000.39	911.52	925.56	38.18	57.24	6.03	47.89	6986.81
2052	6241.24	1074.83	884.20	40.50	64.54	6.51	59.55	8371.38
2059	6483.09	1238.13	1042.84	42.82	71.85	6.99	71.22	8956.94
2066	6724.94	1101.44	1201.48	45.14	79.16	7.47	82.88	9242.51
2073	6966.79	1264.75	1360.12	47.46	86.47	7.95	94.54	9828.08
2080	6508.64	1428.05	1518.76	49.78	93.78	8.43	106.21	9713.65
2087	7450.49	1791.36	1677.40	52.10	101.09	8.91	117.87	11199.21
2094	7692.33	1754.66	1836.04	54.42	108.40	9.39	129.54	11584.78
2100	7934.18	1817.97	1994.68	56.74	115.71	9.87	141.20	12070.35

Source: (Author's construct, 2022).

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Table 4.6: Reference Scenario Projected Water Demand (million cubic meters, Mm^3) for each Sector under RCP 8.5 (2017–2100).

Year	Irrigation	Domestic	Hydropower	Industrial and Commercial	Livestock	Recreational	Institutional and Businesses	Total Water Demand
2017	5032	258.3	91	28.9	28	4.11	1.23	5443.54
2024	6328.62	505.93	299.57	37.46	42.37	5.51	15.47	7234.929
2031	6618.84	701.89	489.94	40.25	51.14	6.08	29.47	7937.61
2038	6909.05	797.86	580.30	33.03	49.91	5.66	33.47	8409.291
2045	7799.21	1184.98	943.23	49.63	74.41	7.84	62.25	10121.55
2052	8737.74	1504.76	1237.88	56.70	90.36	9.12	83.37	11719.93
2059	8096.33	1633.39	1359.98	49.95	90.59	8.79	99.70	11318.72
2066	9414.92	1962.02	1682.07	63.19	110.83	10.46	116.03	13359.52
2073	10450.18	2347.12	2040.18	71.19	129.71	11.93	141.82	15192.12
2080	10812.96	1592.08	1778.14	64.67	130.67	11.65	139.31	14529.47
2087	11175.73	2837.04	2516.10	78.15	151.63	13.37	156.81	16928.82
2094	10538.50	2081.99	2954.06	11.63	152.60	12.09	164.31	15915.17
2100	10901.27	2326.95	2962.02	85.10	163.56	13.81	200.80	16653.52

Source: Author's Construct (2022).

The RCP 4.5 and RCP 8.5 emission scenarios were used to project the combined climate and water use scenarios for each sector as well as changes in water demand. Results from both projected emission scenarios, which are shown in (Figures 4.25 and 4.26) under the RCP 4.5 and RCP 8.5 emission scenarios, respectively, indicate that the basin's water demand will rise in the future (2017-100).

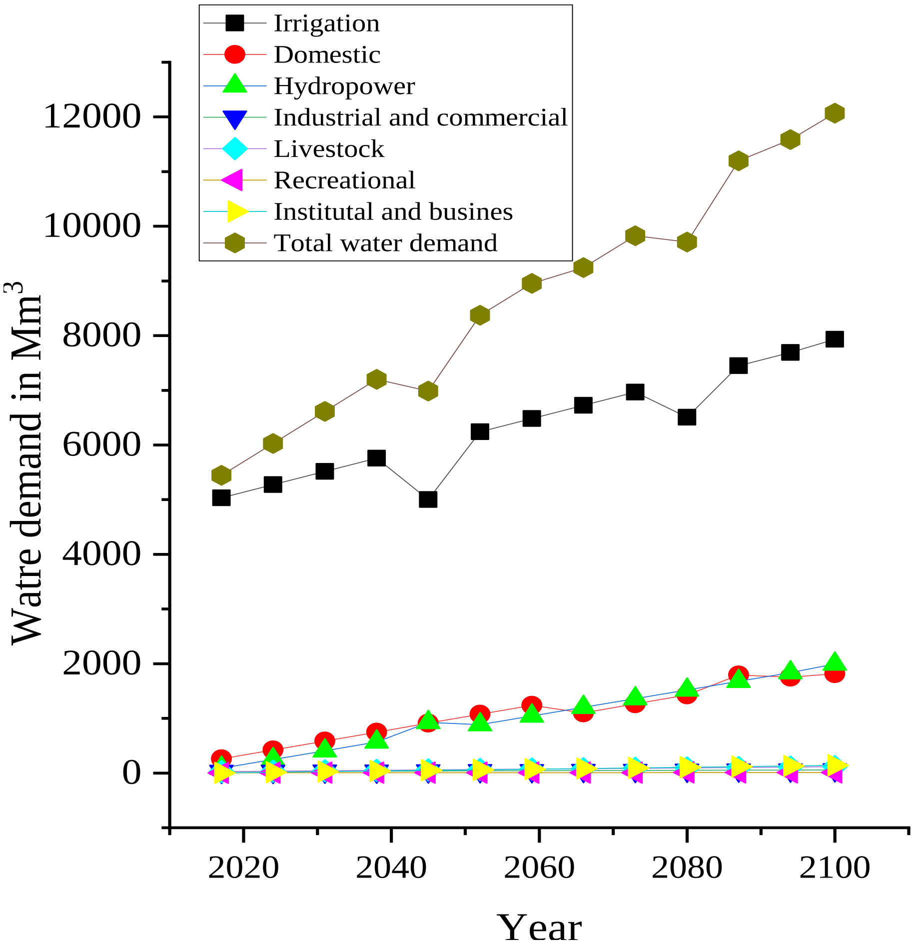

Figure 4.25: Projected Reference Scenario Water Demand (million cubic meters, Mm3) for each Sector under RCP 4.5 Emission Scenarios (2017–2100). (Author's Construct, 2022).

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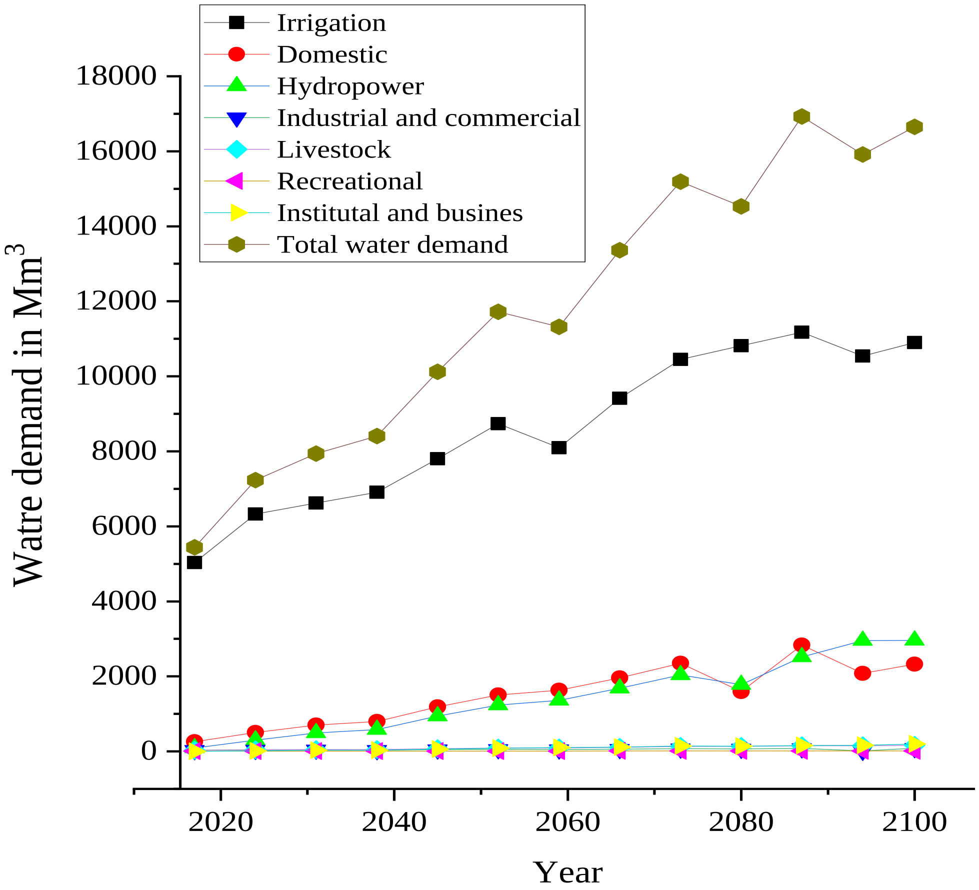

Figure 4.26: Projected Reference Scenario Water Demand (million cubic meters, Mm^3) for each Sector under and RCP8.5 Emission Scenarios (2017–2100). (Author's Construct (2022).

4.7 Discussion

4.7.1 Implications of the Impacts of Climate Change on the Future Evolution of Trend Changes in Hydroclimatic Variables

The RCP8.5 and RCP4.5 emission scenarios were used in this study to evaluate changes in three hydroclimatic variables, including streamflow, temperature, and precipitation, over the reference period (1987-2019) and projections for three (3) additional periods (2017-2100).

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The seasonal air temperature analysis findings, the basin graph lot, and the basin's mean annual air temperature measurements from 1987 to 2019 all demonstrate a distinct and statistically significant upward trend. The changes in the seasonal and yearly mean temperatures showed statistically significant upward trends (0.05) levels. In the river basin, there were two (2) meteorological stations with statistically significant downward trends, two (2) without statistically significant monotonic trends, and eleven (11) stations with statistically significant upward trends.

The results of the trend tests of the projected annual maximum and minimum temperatures in the emission scenarios RCP4.5 and RCP8.5 showed significant upward trends (Figures 4.7, 4.8, and 4.9, respectively) in the three study periods that compared followed the reference period. Under the emission scenarios, RCP4.5 and RCP8.5, the projected mean seasonal temperature for the ensuing three study periods showed strongly increasing trends at the significance level (0.05), indicating a similar trend (Figure 4.10). Temperature increases are anticipated during three seasonal and annual periods. According to the RCP 4.5 and RCP 8.5 emission scenarios, the projected monthly maximum and minimum temperature changes for the short-, medium-, and long-term (2017–2100) show increasing trends.

The results of this study concur with earlier research, which found that the predicted temperature increases for emission scenarios RCP4.5 and RCP8.5 were comparable. The Omo-Gibe River basin will experience increased temperatures in the future, according to a prior study by Chaemiso et al. (2016). Additional studies in the Central Rift Valley, the Ziway River Basin, the Upper Blue Nile Basin (Jema *et al.*, 2018), the Awash River Basin (Taye *et al.*, 2018), and Worku *et al.* (2021) all came to similar conclusions.

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The time series precipitation data from the Eleven (11) weather stations over the study reference period (1987–2019) revealed a declining trend, but the data from the Four (4) weather stations did not reveal any statistically significant trend in either direction. In general, annual precipitation decreased from 1987 to 2019 according to the historical precipitation time series data displayed in (Figures 4.13 and 4.14).

Based on the evaluation of the RCP 4.5 and RCP 8.5 emissions scenarios, a decrease in annual precipitation was predicted (Figure 4.15). The main summer rainy season projections based on RCP 4.5 and RCP 8.5 emissions scenarios, as well as the findings of the spring rainy season trend test (Table 4.3 and Figure 16), showed that precipitation showed a statistically significant negative downward trend over three future periods. Over three-time horizons, short term (2017-2044), medium term (2045-2072), and long term (2073-2100) the projected annual and seasonal precipitation typically exhibit a declining trend. Precipitation is predicted to decrease over three future periods based on the RCP 4.5 and RCP 8.5 emissions scenarios for the period (2017-2100) see (Table 4.3 and Figure 4.17).

Between 1987 and 2019, the streamflow's historical variations were examined. A statistically significant decline (0.05) is shown in Figure 18 for the historical annual streamflow simulation. The evaluation of the projected annual streamflow results indicates that the annual streamflow under the RCP 4.5 and RCP 8.5 emissions scenarios is expected to decrease over time (Figure 19). The results of future seasonal streamflow projections (Figure 4.20) and monthly streamflow projections (Figure 4.21) over three-time horizons short term (2017–2044), medium term (2045–2072), and long term (2073-2100) were evaluated and revealed declining trends. The streamflow projections for the three subsequent future periods (2017–2100) and the historical period (1987–2019) both showed a trend toward decline.

The results of the trend test indicated that the increasing basin temperature over the three research periods and the declining precipitation and streamflow were both statistically significant trends. Future irrigation, hydropower generation, agriculture that depends on rainfall, and another reservoir uses are all anticipated to be impacted.

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4.7.2 Impacts of Climate Change on Temperature

The projected variations in the minimum and maximum temperatures in the river basin were assessed on an annual, seasonal, and monthly basis. On an annual, seasonal, and monthly basis, the river basin's anticipated changes in minimum and maximum temperatures were evaluated. Both climate scenario versions back this up. The baseline was used to compare the projected minimum and maximum temperature changes for climate change scenarios RCP4.5 and RCP8.5. As shown in (Figures 4.7), predictions show that under RCP4.5, annual minimum temperatures will rise by 12.5 °C, 13.07 °C, and 14.5 °C, while under RCP8.5, increases will be 12. 8 °C, 13.81 °C, and 15.01°C cover the following three periods. Projected annual maximum temperatures will increase by 25.05 °C, 26.07 °C, and 27.5 °C under RCP4.5, while RCP8.5 will cause an increase of 25.58 °C, 27.11 °C, and 29.01 °C throughout future periods, as shown in (Figures 4.8) for the future near-term (2017-2044), mid-term (2045-2072), and far-term (2073-2100).

According to projections, monthly mean temperatures will rise by 11.93°C, 11.95°C, and 12.85°C under RCP4.5 and by 13.52°C, 13.91°C, and 15.92°C under RCP8.5, respectively, in the years 2017-2044, 2045-2072, and 2073-2100 (Figures 4.11 and 4.12). Results are expected to show that during the study periods, the average temperature will increase between 2.10 and 3.55 °C under

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RCP 4.5 emission scenarios and between 2.7 and 4.75 °C under RCP 8.5 emission scenarios. From November to May, the average maximum temperature is expected to increase, while it is expected to decrease from June to October. On the other hand, it is anticipated that the average minimum temperature will rise from June to October while falling from November to May. When compared to the baseline period, the anticipated temperature from January to May is higher (Figure 4.5), with hot and dry seasons having higher temperatures and wet and cool seasons having lower temperatures.

Average temperature changes in the Omo-Gibe Basin range from 2.4 to 3.3 °C and RCP 8.5 temperatures range from 2.6 to 4.5 °C. According to studies by Roth et al. (2018) and Chakilu et al. (2020), including those that the basin reported temperature changes to range between 2.04 and 4.15 °C, the end of the 2100 century will be almost identical in direction and rate under RCP 4.5 emission scenarios. Findings from other studies have been confirmed by the findings of this study. According to Nyoni *et al.* (2019), temperature increases in the future are expected to range from 0.07 to 5 °C. Otieno and Anyah (2013), Kopytkovskiy *et al.* (2015), Worqlul *et al.* (2018), and Gao *et al.* (2021) conducted additional studies that focused on the Greater Horn of Africa and projected temperature increases in the future.

In general, Omo-Gibe River Basin average temperature changes under RCP 4.5 emission scenarios range from 2.4 to 3.3 °C, while RCP 8.5 emission scenarios range from 2.6 to 4.5 °C by the end of the 2100 century. According to the combined estimate temperature output, the basin's average and individual models produced in the future periods will increase in comparison to the reference period under the RCP 4.5 and RCP 8.5 emission scenarios. The results of this study suggest that future water shortages will probably get worse due to climate change, which will also probably result in higher temperatures, a worsening of the hydrological cycle, and other effects. Because of how warming temperatures affect soil moisture, surface and groundwater, streamflow, and water availability crops evapotranspiration more water. The findings of the study suggest that the warming trend will continue as temperatures rise, with minimum temperatures rising more quickly than maximum temperatures.

Future precipitation, streamflow, and the amount of water available in the river basin will all be impacted by the anticipated rise in temperature. Depending on the length of the seasonal distribution, the amount of precipitation, the frequency of catastrophic droughts, and other variables, an increase in temperature may result in a decrease in precipitation in some areas, claim Piani *et al*. (2010). The environment is negatively impacted by high temperatures in many ways, including decreased soil moisture content, an increase in the number of hot days while a decrease in the number of cold days each year, an increase in evapotranspiration, and decreased water availability. Streamflow will decrease because for a given amount of precipitation, less rain will reach river streams. Temperature fluctuations, warming, and changes in precipitation will all have an effect on the availability of water. This is in part because it is predicted that higher temperatures will speed up the evaporation process. In the upcoming years, it is anticipated that the Omo-Gibe River Basin will experience greater water stress and warmer temperatures.

4.7.3 Impacts of Climate Change on Future Precipitation

The projected changes in precipitation for the river basin were assessed for the future near-term (2017-2044), mid-term (2045-2072), and long-term (2073-2100) on an annual, seasonal, and monthly scale. During the reference period (1987-2019), the river basin's average annual precipitation was estimated to be 1,200.05 mm and 14,400.70 mm, respectively. On the other hand,

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future forecasts for the near-term (2017-2044), the mid-term (2045-2072), and the long-term (2073-2100) quantify and project future periods of annual total and average precipitation for the river basin. It was quantified and projected that the annual total and average precipitation would be 13060.08, 12089.50, 11869.03 mm, 1090.01, 1007.46, and 999.09 mm, respectively, under the RCP 4.5 emission scenarios and 13058.04, 12017.30, 10791.60, and 1088.17, 1001.44, and 982.63 mm under the RCP 8.5 emission scenarios (Table 4.3).

For the three (3) estimated and projected periods, the amount and distribution of expected climate change effects on future annual precipitation changes are depicted in (Figure 4.14) for the RCP4.5 and RCP8.5 emission scenarios. According to all individual and average regional climate model estimates under the RCP4.5 and RCP8.5 emission scenarios, precipitation decreased over the next three (3) research periods in comparison to the baseline period (Figure 4.13). In the near future (2017-2044), the mid-future (2045-2072), and the far future (2073-2100), it is projected that annual precipitation will decrease by 9.22%, 10.68%, and 12.83% under the RCP 4.5 emission scenarios and by 11.26%, 12.02%, and 13% under the RCP 8.5 emission scenarios, respectively (Figure 4.15).

Precipitation is expected to decrease more under the RCP 8.5 emission scenario than it would under the RCP 4.5 climate change scenario. The results show that the precipitation decreased more significantly under the RCP8.5 scenario than under RCP4.5 in the Omo-Gibe River basin. In comparison to the RCP 8.5 emission scenarios, the projected decreases in mean annual precipitation for the RCP 4.5 emission scenarios range from 10.77 to 13.11%. The mean monthly average precipitation was predicted to decrease by 9.5-12.6% and 11.6-13.8%, respectively, for the study periods under the RCP 4.5 and RCP 8.5 emission scenarios (Figure 4.17).

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According to the RCP 4.5 emission scenarios, the monthly average precipitation change during the summer's main rainy season and the irregular rainy season will be 10.12 to 12.7% and 11.4 to 13.55 %, respectively, while it will be 10.13 to 13.18 and 12.08 to 14.5 % under the RCP 8.5 emission scenarios. Under RCP 8.5 emission scenarios, the window (2073-2100) is expected to have the largest annual precipitation decrease in comparison to the other two (2) study windows in the basin (2045-2072) and (2017-2044). The Omo-Gibe River basin has two (2) distinct rainy seasons: a minor rainy season from June to August and a regular rainy season from March to May. Under the two (2) emission scenarios as well as during the study periods, the irregular rainy season, which lasts from March to May, experiences greater declines than the main rainy season, which lasts from June to August.

The reductions in precipitation should be unidirectional under the RCP 4.5 and RCP 8.5 emission scenarios. The findings of this study are consistent with previous studies' forecasts of future precipitation declines (IPCC, 2014; Hasan et al., 2018; Osima et al., 2018). Under the RCP4.5 and RCP8.5 emission scenarios, it is anticipated that future precipitation in the river basin will decrease, both during the regular rainy season from March to May and during the main summer rainy season from June to August. The results of this study, which are in agreement with previous studies (Jaiswal et al., 2017), show that precipitation or the amount of seasonal precipitation decreases as a result of climate change Other studies have produced comparable findings in response to predicted precipitation declines brought on by climate change (Peleg et al., 2014; Samuels, 2014), as well as a predicted decline in East Africa's precipitation by the end of the twenty-first century (Christiansen et al., 2007; IPCC, 2013).

The Omo-Gibe River Basin's two rainiest seasons are spring (March- May) and summer (June through August). These rainy seasons are the most important ones in the river basin because they significantly affect past, present, and projected seasonal and annual precipitation patterns, as well as significantly contribute to precipitation and the hydrological driver. The magnitude of the seasonal streamflow will be influenced by the amount of precipitation expected to cause a future decline in streamflow. It has a sizable impact on the amount of streamflow in the river basin as well. Significant irrigation projects have been built in the Omo-Gibe basin, including three (3) already-existing dams, a fourth dam that is currently being built there, and a fifth dam that is planned, increasing irrigation. As a result, the basin's streamflow, available water, hydropower generation, irrigation methods, agricultural output, pasture for the lowland nomadic populations community livelihoods, drinking water, livestock water, and rain-fed agriculture will all be affected by the decrease in precipitation and increase in temperature during these months.

Statistically significant correlations between temperature and precipitation were found in this study's findings, indicating that precipitation is likely to worsen and become less frequent in the future. Less precipitation will occur as a result of the anticipated worsening of climate change, which will alter its frequency, total amount, and spatial and temporal distribution. As a result, the relationship between precipitation and temperature has a direct bearing on future streamflow and water availability in the river basin.

4.7.4 Impacts of Climate Change on Future Streamflow

Using the SWAT model, it was determined whether the future streamflow would be impacted by climate change under the RCP 4.5 and RCP 8.5 emission scenarios. The potential future impacts of climate change on streamflow were calculated using bias-corrected climate input data from a

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mean of fifteen (15) RCM ensemble models. The three-window streamflow's reference period and projected future periods were contrasted. The projected streamflow for the river basin over the ensuing three (3) time periods—short-term (2017-2044), mid-term (2045-2072), and long-term (2073-2100)—indicates a decline in the river basin in accordance with the RCP 4.5 and RCP 8.5 emission scenarios (Figure 4.19).

Future streamflow changes for the river basin were assessed and predicted on an annual and seasonal basis. Project future streamflow magnitude declines for each scenario over three (3) subsequent periods from the baseline period (Figure 4.13). In the future near-term (2017-2044), mid-term (2045-2072), and far-term (2073-2100) periods, the annual average streamflow is projected to decrease by 405.7 m^3/s, 395.8 m^3/s, and 375.6 m^3/s under the RCP 4.5 emission scenarios, and by 390.4 m^3/s, 380.6 m^3/s, and m^3/s under the RCP 8.5 emission scenarios, respectively, from the baseline period annual average streamflow 428.58 m^3/s. While the projected reduction under RCP 8.5 emission scenarios is 10.9-12.8% over the three (3) study periods, the projected reduction under RCP 4.5 emission scenarios is in the range of 7.0-10.9% for the annual average streamflow decrease. Seasonal streamflow is expected to decline by 3.5-4.2% and 3.1-7.5% under the RCP 4.5 and RCP 8.5 climate change scenarios, respectively, with two (2) rainy and hot and dry seasons. For the study periods, the largest ranges of monthly average streamflow decline under RCP 4.5 and RCP 8.5 are, respectively, 10.5-13.6% and 12.6-14.8%.

For the short term (2017-2044), the medium term (2045-2072), and the long term (2073-2100), the highest monthly average streamflow decreases were predicted by the RCP 4.5 emission scenarios to be 410.7 m^3/s, 400.8 m^3/s, and 380.6 m^3/s, respectively. However, the highest decreases were predicted by the RCP 8.5 emission scenarios to be 400.4 m^3/s, 390.6 m^3/s, and

370.8 m^3/s, respectively. The predicted annual average streamflow change decreases between 7.08 and 10.99% under the RCP 4.5 emission scenarios and between 10.98 and 12.88% under the RCP 8.5 emission scenarios during the driest autumn (September to November), warmest winter (December to February), wettest summer (June to August), and irregular rain season (March to May). According to the RCP 4.5 scenario and the RCP 8.5 emission scenarios presented in (Table 4.4), the predicted monthly average streamflow changes during the driest autumn (September to November) and the hottest winter (December to February) decreases range from 4.02 to 6.22%, and 6.52 to 8.00%, respectively. According to (Table 4.4), under the RCP 4.5 emission scenarios and the RCP 8.5 emission scenarios, the predicted monthly average streamflow changes for the summer rainy season and irregular rainy seasons range from 3.00 to 4.77% and from 4.46 to 4.88%, respectively. The estimated and anticipated seasonal streamflow, which is expected to change and decrease during the two (2) rainiest seasons as well as the driest and hottest seasons, is likely to follow the predicted precipitation pattern.

The study's findings indicate that the streamflow in the river basin will likely decline in the future. According to Kabobah *et al.* (2016), streamflow will change and decline as a result of climate change and its dependence on precipitation. The results of this study support the assertion made in a related study that anticipated decreases in precipitation will be related to future declines in streamflow (Saeed *et al.*, 2022). This study's conclusions that streamflow changed and decreased under the RCP 4.5 and RCP 8.5 global emissions scenarios are consistent with earlier findings (Amisigo *et al.*, 2016). Similar research was done by Bessah *et al.* (2020), who found that future climate change effects may result in a decrease in mean annual streamflow. The research's findings are consistent with other studies' predictions that streamflow will decrease due to climate change (Khoi and Suetsugi, 2012; IPCC 2014; Hoan et al., 2020). A study done in Ethiopia indicates that

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streamflow will decrease in the future (Ayalew, 2019). This study supported earlier findings that, under both RCP 4.5 and RCP 8.5 climate emissions scenarios, streamflow during rainy seasons would decline significantly in the future (Shrestha *et al.*, 2018; Kim and Choi, 2013).

RCP 8.5 climate change scenarios are predicted to result in the largest predicted decrease in streamflow, according to Emami and Koch (2019). The predicted streamflow decreases are more noticeable in the hot, dry autumn (September to November) and winter (December to February) seasons than in the wet seasons, especially from January to April. The findings of this study are consistent with earlier hypotheses about the anticipated seasonal decrease in streamflow (Sanikhani *et al.*, 2018), which has been shown in numerous studies to be a result of climate change. The results of other studies, which indicated an overall longer and drier dry season, corroborated the study's conclusions regarding the seasonal distribution of precipitation. According to Ngo *et al.* (2018), Huang *et al.* (2018), and Oeurng *et al.* (2019), a decrease in precipitation was the main cause of future streamflow declines. Climate change will result in future streamflow decreasing, according to a different Ethiopian study (Takele *et al.*, 2021). This study, which supports that of the (IPCC, 2013), also demonstrates a decrease in streamflow as a result of modifications in the precipitation and evaporation regimes brought on by climate change.

According to the research findings mentioned above, the combined effects of rising temperatures and decreasing precipitation will have an impact on streamflow. The results of the study indicate that streamflow is significantly influenced by temperature and precipitation. The findings of both studies Saha and Zeleke's (2015) assessment of the effect of climate change on streamflow and this study are in agreement. The study's findings will have a big impact on how streamflow will change in the future. The study's results also show a significant relationship between streamflow,

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temperature, and precipitation. It is anticipated that streamflow will drop less during the summer rainy season than it does during the erratic rainy season. The two (2) rainy seasons will see a rise in temperature and a decrease in precipitation, which will have an impact on the basin's streamflow. The magnitude of the seasonal streamflow will decrease more sharply during the upcoming two (2) hot and dry seasons than it will during the upcoming two (2) wet seasons. The amount of precipitation has a greater effect on streamflow magnitude during the two (2) rainy seasons and annually than it does during the hot and dry seasons. The projected streamflow is significantly reduced in two (2) scenarios, RCP 4.5 and RCP 8.5, for each of the three (3) research periods, including the hot, dry, and wet seasons. Substantial variations in precipitation amounts and patterns are the primary factors affecting changes in river streamflow. Eventually, there might be less water available in the river basin for different uses as a result of this.

According to this study's findings, streamflow will decrease when there is less precipitation and more heat. Temperature increases in response to decreased precipitation, illustrating the close relationship between the two (2) elements and restricting future streamflow in the river basin. Future streamflow predictions for the river basin indicate a decline in both annual and seasonal streamflow. This study demonstrated that there is a great deal of uncertainty regarding the streamflow in the Omo-river basin in the future. The basin is investigated under the two (2) emission scenarios RCP 4.5 and RCP 8.5. Streamflow, precipitation, and temperature increases are all affected by these scenarios. Climate change may cause water shortages in the basin, according to a summary of findings evaluated under emission scenarios RCP 4.5 and RCP 8.5, which represent the highly uncertain future streamflow. The Omo-Gibe River basin has previously experienced water shortages for both other water uses and the hydroelectric power generation sector. Due to the decreased streamflow, it is predicted that the precipitation and streamflow

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reductions will be more severe than the previous water shortage. As a result, hydropower, irrigation, and water availability may be more negatively impacted than other basin-wide sectors.

4.7.5 Impacts of Climate Change on Future Water Availability

Future reductions in water availability and river streamflow are expected to be brought on by climate change. River basin authorities, engineers, planners, and managers, as well as those in charge of managing water resources, need accurate projections of future water availability in the basins to help with making adaptive management decisions and lessen the effects of climate change. To meet this need, the SWAT model was used in this study to forecast future streamflow and subsequent water availability. The annual total water availability in the river basin could decrease between three (3) study periods compared to the reference period by between 8.0 and 25.1% as a result of future climate change effects. Under the RCP 4.5 emission scenario, annual total maximum water availability is predicted to decline by 8.13-20.3%, while under the RCP 8.5 emission scenario, it will decline by 12.1-24.6%. In the future, the RCP 4.5 emission scenario predicts a 6.13% decrease in water availability during the hottest and driest seasons (September through November) and winter (December through February). The predicted water availability decreases by 4.11 % under the RCP 4.5 emission scenario while 7.12 % under the RCP 8.5 scenario throughout the summer rainy season (June August) and the irregular rainy season (March to May). The RCP 8.5 emission scenario is projected to show a greater future reduction in water availability for all study periods compared to the RCP 4.5 emission scenario for the three (3) study window periods.

The results of this study confirm those of earlier studies that show that the Basin's water availability has decreased due to the effects of climate change. For instance, climate change will result in less

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water being available in the future (Versini *et al.,* 2016). Climate change and future precipitation declines will result in less water being available in the Basin (IPCC, 2014). According to another study Harding *et al.* (2012); Ficklin, (2013); Hasan *et al.* (2018), the effects of climate change will affect the amount of water that is available in the future. Water availability in the Zarrine River Basin will decline as a result of the effects of climate change, according to other studies that used the SWAT model (Emami *et al.,* 2019). The results of this study are in line with previous research that projects temperature increases, drier summers, wetted winters, and decreased water availability (Arnell, 2011). According to projections, the river basin's summer rain season (June - August) and erratic season (March-May) will experience smaller percentage decreases in streamflow magnitude than the winter (December-February) and the drier and hotter seasons (September-November).

The study's findings state that predictions of temperature, precipitation, and streamflow patterns will probably reflect estimates and projections of water availability for the upcoming year and each season. Three (3) research periods, two (2) wet seasons, and hotter and drier seasons are predicted to cause it to fluctuate and decline. Rising global temperatures and shifting climatic influences will likely cause changes to the hydrological conditions and water cycle in the river basin. The amount of water that is available in the Omo-Gibe River basin is anticipated to decrease as a result of future streamflow reductions, future precipitation that falls throughout the two (2) rainy seasons in general, as well as the drier and warmer seasons. The study's findings indicate that the combined effects of climate change, rising temperatures, declining precipitation, and streamflow magnitude will cause a decrease in the amount of water available in the Omo-Gibe River Basin in the future.

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4.7.6 Impact of Climate Change on Future Water Availability for Irrigation and Hydropower Generation

Around the world, irrigation is crucial for crop production, and hydropower is one of the main sources of renewable energy. Crop growth, irrigation, and hydroelectric energy production are all directly impacted by the hydrological cycle and the availability of water supplies. Climate change is expected to have an impact on the amount of water available for irrigation and hydropower production. Future water availability for irrigation and hydropower generation, a crucial input for both, was evaluated and projected in this study using a quantitative approach. This study aimed to estimate and project the future availability amount of water for irrigation and hydropower generation under various climate change scenarios, and the future individual sectors and total water demand were calculated under two (2) climate scenarios shown in (Figure 4.25, Figure 4.26, Table 4.5, and Table 4.6). The estimated total unmet demand in the river basin is projected to be around 5631 M m^3 due to increased demand across all sectors (Figure. 4.24). In estimated individual sectors, the total unmet hydropower demand of 1,692.94 M m^3 (30.06 %) and unmet irrigation demand of 1,110.48 M m^3 (19.72 %), the impact of any future demand will grow, and climate change are likely to be severe. Three (3) other sectors will be affected by the unmet scenario: unmet domestic demand of 1143.14 M m^3 (20.30 %), unmet industrial and commercial demand of 368.23 M m^3 (6.53 %), and unmet livestock of 1159.47 M m^3 (20.59 %). In this scenario, however, the institutional, commercial, and recreational water requirements are not met by 81.65 M m^3 (1.45 %) and 76.2 M m^3 (1.35 %). The results of the study showed a decrease in streamflow and precipitation. Therefore, the two (2) rainy seasons, as well as the hot and dry seasons, will exacerbate water shortages in the future. Water shortages could occur during the major and erratic rainy seasons as well as the warm and dry seasons, according to projections made under the RCP

4.5 and RCP 8.5 emission scenarios. Between January and March, there is a greater water shortage than during either of the two rainy seasons, which last from May through September. The RCP 8.5 emission scenario is expected to cause the water shortage to worsen more than the RCP 4.5 emission scenario.

Due to increased irrigation, hydroelectric power generation, domestic water use, livestock, population growth, and agricultural expansion, water scarcity is expected to increase from 6.0% to 30.6%. According to the estimated increase in water demand, water scarcity for irrigation could increase between 12.2% and 20% in RCP 4.5 emission scenarios and between 15.5% and 25.5% in RCP 8.5 emission scenarios throughout the study period. As a result of rising water demand, projected results indicate that water scarcity for hydroelectric power generation could rise between 9.5 and 15.2% during the study periods under RCP 4.5 emissions scenarios and between 12.5 and 20.4% during RCP 8.5 climate change scenarios. Under the RCP 4.5 and RCP 8.5 climate change scenarios, respectively, over the three (3) research periods, increases in water scarcity, hydroelectric generation, and irrigation change range between 7.9 and 12.5%, 13.4 and 18.2%, 18.5 and 23.1%, and 26.2 and 30.6%.

The results of this study corroborate those of earlier studies. For instance, the effects of climate change in the future will increase the demand for water and make it scarcer (Dettinger *et al.*, 2004; Clow, 2010). The effects of climate change exacerbate water shortages on a regional and global level (Du *et al.*, 2021). According to Jakimaviois *et al.* (2020), the effects of climate change could reduce streamflow, which would reduce the amount of water available for the hydroelectric power generation process. The energy shortage during the dry season is significantly impacted by its effects, claim Hasan *et al.* (2020). Climate change is anticipated to reduce water availability in the

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future, which will result in less electricity being generated (Anghileri *et al.*, 2018). Climate change will have an impact on the irrigation industry due to water shortages (Dawit *et al.*, 2020). Climate change's future effects mean that there won't be enough water available to meet the needs of the irrigation system (Allani *et al.*, 2020). Climate change predictions indicate that irrigation water resources will likely become very limited in the future (Nguyen *et al.*, 2016).

The Omo-Gibe River Basin (Ethiopia) may experience future climate change impacts that worsen and intensify water shortages more than other sectors, including industrial and commercial, livestock, institutions, businesses, and leisure. The quantified and anticipated results suggest that climate change may have an impact on future hydropower generation, annual and seasonal streamflow, and basin water availability conditions. Hydropower plants will generate significantly less power during the dry season than they will during the upcoming rainy season, and the irrigation sector will produce significantly lower agricultural yields during the dry seasons than they will during the upcoming rainy season due to the future effects of climate change and the lack of adequate water availability.

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The Omo-Gibe River basin's average future temperature is predicted to rise by 2.6 to 3.2 °C, while future precipitation, streamflow, and water availability are all predicted to decrease relative to the reference period by 7.4 to 24.7%, 7.4 to 24.7%, and 8.0 to 25.1%, respectively. As a result of the basin's anticipated 8.0% to 25.1% increase in water scarcity, the availability of water for irrigation and hydroelectric generation will decline from 15.5 to 25.4% and 10%.5 to 20.2% respectively during the study periods. The SWAT and WEAP models were successfully coupled in this study to simulate and forecast hydrological processes and water availability. Using the outcomes of these simulations and projections, it is possible to make predictions about how climate change will affect the amount of water available for irrigation and hydropower production and adaptation options to climate change, and coping with the impacts of climate change.

4.8 Unexpected Uncertainty in Future Projected Water Availability for Irrigation and Hydropower generation

The future impact of climate change on water availability is still very unclear (Strzepek and Mccluskey, 2010). The short-, medium-, and long-term temperature rise and precipitation decline (2017-2044, 2045-2072, and 2073-2100) are quantified and projected in this study, along with the effects of climate change that resulted in a decline in streamflow and water availability (supply).

Without options for coping with climate change, projections of water availability and demand for the end of the twenty-first century indicated that the basin would face severe water shortages. Options for adaptation are put forth to deal with and lessen the effects of climate change and increase resilience to possibly more drastic changes in hydrological conditions. The quantification and projection of future water availability for irrigation and hydropower generation, as well as an evaluation and forecast of the distribution of water demand, served as the foundation for this study's identification of climate change adaptation options. The river basin has been able to manage and lessen severe water shortages while reducing the impact of climate change by implementing options for climate change adaptation for future water availability.

Numerous factors influence water demand, such as population and livestock growth, economic development, climate change, land use change, technological advancements, lifestyle changes, developments, expansion of irrigation and hydropower, industrial and commercial growth, and growth in leisure, institutions, and businesses, among others. The impact of climate change on water demand for irrigation and hydroelectric power generation, however, is the only topic covered in this study. Due to the limited and scarce potential water availability as a result of future climate change impacts, this study suggests adaptation options. The other seven (7) water use sectors listed in (Table 4.5, Table 4.6, Figure 4.25, and Figure 4.26) and climate change will also contribute to an increase in water demand in the river basin over the ensuing decades.

Because there aren't enough water resources, decreasing either water supply or demand won't be sufficient to meet the escalating demand. It is advised to use a water management system with methods for controlling water supply and demand that can account for shifting climatic conditions, rising water demand, and associated uncertainties.

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4.9 Expected Future Water Resource-Related Impacts of Climate Change

The global hydrological cycle is altered by global atmospheric warming (UN, 2010; Taylor *et al.*, 2013), and its potential intensification alters the fundamental hydrological regimes due to the rise and fluctuation of the surface temperature. One of the biggest effects of climate change on the availability of water is this. As a result, it has the potential to influence and alter precipitation patterns and intensity. On the other hand, their effects can impact and alter the streamflow in the river basin region. These changes, which have an impact on a wide range of water resources and are likely to increase future water scarcity and water demand in the river basin, can have an impact on the availability of water.

According to Stocker *et al.* (2013), the main effects of climate change on hydrology are rising and shifting global surface temperatures in response to shifting precipitation and water availability. The interdependence and inherent variability of temperature, precipitation, and water availability have always made it difficult for human activities that depend on them to adapt. Adopting strategies to address changes in temperature, precipitation, and water availability is urgently needed to predict and mitigate threats posed by the high degree of uncertainty associated with the future effects of climate change. Resilience, which requires the capacity to adapt to and recover from the effects of climate change, is necessary to deal with the growing unpredictability and future impacts of climate change, as well as unexpected future water scarcity and increased water demand. Three (3) of the main stresses that will be placed on the water sectors as a result of future climate change are water scarcity, availability, and demand.

The river basin is expected to experience increased water demand and shortages as a result of climate change. However, it is anticipated that the demand for and supply of irrigation water will be more impacted by climate change than in other areas. This is because irrigated agriculture continues to use more water than any other sector, surpassing demands from homes, hydroelectric power plants, businesses, industries, livestock, recreation, institutions, and homes.

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4.10 Possible Global Adaptation Options to Climate Change and Coping with the Impacts of Climate Change

The two main approaches to combating climate change are mitigation and adaptation, and both are crucial for coming up with solutions and showing others how to do it. Mitigation strategies reduce GHG concentrations by reducing GHG emissions and increasing carbon sinks, which slows climate change and reduces the likelihood of extreme events (IPCC, 2001; Lu, 2013). Adaptation, in the context of the IPCC (2001); Pan and Zheng (2010); IPCC (2014), is the application of regulatory strategies in response to a real or anticipated climate stimulus. As a result of the observed or anticipated effects of climate change, adaptation also includes changing or modifying something to suit a purpose in addition to adapting natural or human systems and reducing vulnerability or enhancing resilience.

This study's main objective is to identify and lay out mitigation strategies for the anticipated impacts of climate change (drivers) on future water availability for irrigation and hydropower generation. In this basin, there are fewer opportunities to reduce emissions, which increases the significance of adaptation measures. Regional adaptation strategies, however, are more desired as mitigation becomes more expensive and advantageous (Wilbanks et al., 2007; van Vuuren et al., 2011). Globally, mitigation has greater net costs and advantages than local mitigation.

4.11 Identifying Climate Change Adaptation Options for the Future Availability of Water for Irrigation and Hydroelectric Power Generation

In this study, two (2) various adaptation-based strategies were investigated. These climate change adaptation options include, for example, "no-regret strategies" on the supply and demand sides of

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the water equation as well as options related to understanding and controlling impacts. These include coming up with practical solutions, reducing the risks brought on by climate change impacts, boosting sector resilience, lowering water security concerns, increasing water supply, and managing demand and use.

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The adaptation choice of one has an effect on other water sectors. When irrigation is increased to reduce crop losses brought on, for instance, by rising temperatures and changing precipitation patterns and amounts, it leads to a higher demand because there is less water available for hydroelectric power generation. In this study, the water allocation and demand for seven (7) different water sectors were evaluated (Figures 4.22 and 4.23) and projected under the emission scenarios RCP 4.5 and RCP 8.5, respectively, in comparison to the baseline period (Figures 4.22 and 4.23) and suggested options for both water supply- and demand-side climate change adaptation.

4.12 Water Supply and Demand under no regret's Climate Change Adaptation Options

A system that only offers one option to combat climate change is usually less prepared to handle uncertainty than a system that offers a number of options. Because of this, combining the two adaptation strategies is more sustainable than doing so separately (Magini et al., 2008). In this study, two (2) climate change adaptation strategies—supply-side water enhancement and demand-side water efficiency—should be taken into account in order to predict future water availability for irrigation and hydropower production. Water supply is defined in this study as the capacity to provide water for river basin irrigation and the generation of hydropower. Water demand is the amount of water required for irrigation and the generation of hydropower. Reduced water losses and significantly increased water use efficiency must be given top priority.

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4.12.1 Opportunities for Adaptation for Future Irrigation Water Management

There are no regrets options for the water supply side of climate change adaptation, according to the IPCC report from 2007. These options include finding and extracting groundwater, increasing stormwater storage, increasing storage capacity by building dams and reservoirs, removing invasive alien vegetation from riparian areas, and water transfer.

Reduce consumer demand, enhance technical efficiency in water use, boost water use efficiency, and effectively distribute available water among competing uses to avoid regretting addressing the water demand side of climate change adaptation strategies (IPCC, 2007). The water demand-side no regrets adaptation options listed by IPCC (2007) include changing the cultivation calendar, crop combination, irrigation method, and area planted. Other options include importing agricultural products or "Virtual water," encouraging indigenous agricultural practices for sustainable water use, and increasing the use of water.

The IPCC (2001) claims that adjustments can be made to future irrigation water availability in terms of water supply, most notably by expanding irrigation sources' capacities. In response to climate change, Kundzewicz *et al.* (2007) identified other opportunities for adaptation options on the water supply side for future irrigation water availability options, such as groundwater abstraction, increased storage, and expansion of reservoirs, seawater desalination, stormwater reclamation, and water transfer between river basins.

IPCC (2001) also shows potential for climate change adaptation on the water demand side, increasing irrigation use efficiency, creating drought-tolerant varieties, and changing cultivation patterns. In response to climate change Allan (1998) and Arnell and Charlton, (2009) identified additional opportunities on the water demand side for future irrigation water. These possibilities include enhancing water efficiency and water recycling, lowering irrigation requirements by altering crops or farming methods, and lowering demand by supplying agricultural products.

4.12.2 Opportunities for Adaptation for Hydropower Generation Water Management

Production of hydropower is significantly impacted by both water storage in dams and a lack of water to drive turbines and hydroelectric plants. This has happened because of changes in streamflow brought on by a rise in air temperature and a fall in precipitation. In response to the effects that climate change is anticipated to have on the supply and demand sides of water for future hydroelectric power generation, the authors listed here offer both structural and non-structural adaptation solutions (USAID, 2007; UNECE, 2009; Blackshear *et al.*, 2011; US Energy Information Administration, 2010; COWI, 2013; COWI, 2013; ISRBC, 2013).

1. Structural Options for Adaptation for Future Hydropower Generation Water Management

- Flexible construction of the installation capability.
- Construct robust dams with large reservoirs to cope with extreme events.
- Many uses for the reservoir should be taken into account before it is built or expanded, including irrigation, the production of hydropower, the supply of drinking water, tourism, and others.
- The structural features of the dam can be enhanced by changing the number of turbines, adding a new reservoir, altering the spillways, and re-routing tributaries upstream to prevent discharges into watercourses.

2. Non-structural Options for Adaptation

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- Establishing guidelines for incorporating environmental considerations into the operation of current hydroelectric power plants, such as increasing the efficiency and streamflow regulation of existing plants, as well as designing and constructing new hydroelectric power plants.
- Updated climate and hydrological predictions.
- Investigating potential future capacity gains or losses in a particular river basin area.
- Increase hydropower output to handle peak loads and better match the supply of electricity with consumer demand.
- A detailed strategy for handling water resources and emergencies.
- Considering climate change in the operation and management of the hydroelectric power system for generation, transmission, and distribution.
- Detailed analysis for accurate long-term climate change projections.
- Enhancing the effectiveness of power plant operation and maintenance.
- Depending on future capacity increases or decreases experienced by a specific reservoir or river basin.
- Substituting energy-efficient lighting for incandescent lighting.
- Find and use a variety of renewable energy sources, such as hydropower instead of solar or wind farms.
- Establish a reporting requirement that requires all hydroelectric companies to provide comprehensive operational data on rivers and discharges to enhance monitoring records in the future.
- Develop new, affordable designs or alter existing ones to address hydroelectric power generation issues specific to a particular site.

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- Create new, cost-effective designs and alter those that are currently in use to address specific issues with a hydropower generation site.
- Regular evaluations of hydropower permit requests, streamflow patterns, seasonal minimum, and maximum water levels, sufficient reservoir capacity to handle flooding during the rainy season, and connections to river basin management plans.

Options for addressing climate change must consider significant environmental costs, non-environmental operating and capital costs, as well as future water availability for irrigation and the production of hydropower, if they are to be effective on both the supply and demand sides of the issue. Dam, reservoir, and other hydraulic structure construction affects ecosystems and results in habitat destruction. Integrated water resource management in river basins is becoming more and more important for the availability of water management in the future on both the supply and demand sides because it reduces operational costs, capital expenditures, and environmental degradation.

4.12.3 Integrated Water Resource Management (IWRM) and Climate Change Adaptation Options

According to the Global Water Partnership (GWP), IWRM is a process that promotes the coordinated development and placement of water, land, and related resources to maximize economic and social well-being equitably without jeopardizing the sustainability of significant ecosystems. IWRM in the river basin improves the management of land and water needed for irrigation, domestic use, hydropower generation, and other water uses.

IWRM offers a wide range of tools and methodologies that incorporate tactics that specifically address information flow barriers, address access to water, address ecosystem integrity, and

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preserving water quantity and quality for future generations. IWRM, for instance, can assist communities in adapting to changing climatic conditions that might reduce the amount of water available or cause severe floods or droughts (Cap-Net, 2009). IWRM also aids in adaptation to variations in the river basin's water supply. Risks can be effectively identified and mitigated during the reservoirs, dams, other water structures, and basin planning phase. When action is needed, stakeholder engagement helps mobilize communities and take action. Water users could be encouraged to make more responsible use of the resource in the face of changing water availability conditions due to climate change.

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CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusions

The impact of climate change on the future availability of water for irrigation and hydroelectric power generation in the Omo-Gibe River Basin was quantified and projected in this study. Climate change projections based on output data from CORDEX-Africa's fifteen (15) RCM multi-model ensemble models for the RCP4.5 and RCP8.5 emission scenarios precipitation and temperature were downscaled over three (3) timescales: short-term (2017-2044), medium-term (2045-2072), and long-term (2073-2100), and data from climate model outputs were bias-corrected using the quantile mapping method. By using the SWAT model to generate streamflow input data for the WEAP model and calibrating and validating the models, the SWAT and WEAP coupled hydrologic models were used to quantify and project future water demand, water allocation, and water availability. It is essential for the long-term management of water resources, minimizing the effects of climate change, and developing options for and strategies for adaptation. The study estimated and quantified the effects of climate change on hydrometeorological variables to offer strategies for mitigating climate change and guaranteeing that there will be enough water for irrigation and hydropower generation in the future.

Over the three (3) research periods, estimated and expected annual, seasonal, and monthly temperature changes significantly increase in comparison to anticipated annual, seasonal, and monthly changes in precipitation and streamflow. RCP 4.5 and RCP 8.5 indicate that the seasonal and annual temperature forecasts exhibit a statistically significant upward trend. Predictions for

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annual and seasonal runoff and precipitation do, however, show a statistically significant negative downward trend under RCP 4.5 and 8.5 emission scenarios, and they do so in a generally downward direction.

The results show that temperature increases under RCP4.5 emission scenarios would range from 2.6 to 4.5 °C, whereas under RCP4.5, they would be between 2.4 and 3.3 °C. Under RCP 4.5 emission scenarios, the predicted decrease in precipitation ranges from 10.7 to 13.6%, while under RCP 8.5 emission scenarios, it ranges from 11.1 to 13.8%. Under RCP 4.5 emission scenarios, the expected reduction in annual average streamflow is between 7.0 and 10.9%, while under RCP 8.5 emission scenarios, the reduction is between 10.9 and 12.8%. In comparison to the baseline scenario, the impact of climate change could result in an increase in future water shortages of 8.0 to 25.1%, with the majority of these shortages occurring during the hot and dry season from November to March. . Water availability for irrigation and the production of hydroelectric power will decrease over the study periods, with decreases of 15.5% to 25.4% and 10.5% to 20.2%, respectively. Between 7.9% and 30.6%, more water will be scarce due to the combined effects of climate change and rising water demand.

The results of the study indicate that the first and largest potential river streamflow will likely decrease as a result of the effects of climate change, which will result in less water being available in the river basin. Over three (3) study periods, it is possible to significantly reduce the amount of water that is available in the river basin for irrigation and hydropower. Water availability for a variety of uses including domestic, industrial, and commercial sectors, livestock, recreation, institutions, and businesses, will be significantly impacted by climate change. Climate change will put tremendous pressure on the basin's water resources, water availability, and water-related industries. Under the RCP 4.5 and RCP 8.5 emission scenarios, it is anticipated that the average

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air temperature will increase, but that precipitation, streamflow, and the amount of water available in the river basin will all likely decline. The Omo-Gibe River Basin's water supply for irrigation and hydroelectric power generation is expected to decline significantly under the RCP 4.5 and RCP 8.5 emission scenarios, according to estimates.

The Omo-Gibe River basin's future precipitation, streamflow, and access to the resulting water are all subject to significant uncertainty, according to this study's findings. Using two (2) emission scenarios based on the RCP 4.5 and RCP 8.5, a thorough method for high uncertainty and high consensus that the effects of future temperature increases will affect future precipitation amounts, streamflow magnitude, and the availability of the resulting water is used for irrigation and hydropower generation in the basin is investigated. A summary of the study's findings indicates that the effects of climate change may lead to water shortages in the basin in the future. Because of low streamflow and precipitation, water availability is expected to be lower than in previous years. This may have a greater impact in the basin's water-related areas, such as irrigation and hydropower production, than in other areas.

Changes in precipitation and temperature have an immediate impact on streamflow. Expected changes in temperature and precipitation, however, have a significant impact on expected changes in streamflow Future climate change will result in significant increases in annual, seasonal, and monthly temperatures as well as decreases in precipitation and streamflow in the Omo-Gibe River basin. Streamflow is predicted to decrease as temperatures rise and precipitation decreases. Streamflow, precipitation, and temperature all had a statistically significant relationship with one another. There was a statistically significant correlation between streamflow, precipitation, and

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temperature. Streamflow, precipitation, and temperature were correlated in a statistically significant way.

The projected streamflow and consequent reduction in water availability in the basin are predicted by RCP4.5 and RCP8.5 emission scenarios to occur during hot and dry seasons, as well as summer and unpredictable rainy seasons. Future climate change is anticipated to have a particularly negative impact on the irrigation, residential, hydroelectric, industrial, and commercial sectors in the basin, as well as the livestock, housing, and residential sectors. Unmet water demand and water shortages are expected to get worse in these sectors as a result of rising temperatures, declining precipitation, river streamflow, and other water availability-affecting factors. The irrigation, hydroelectricity, and agricultural sectors of the Omo-Gibe River Basin, which are vital to the nation's economy, may be significantly more challenging as a result of this type of change. Overall, the study's conclusions offer useful information for putting good water management practices into place and creating strong future climate change adaptation options and strategies to lessen water scarcity and the effects of climate change in the river basin. As a result of the anticipated future water shortage brought on by the effects of climate change, it is necessary for irrigation, agricultural production, hydropower generation, and upstream and downstream water needs.

Under future climate change, it is anticipated that precipitation, streamflow, and water availability will all be less abundant than they were during the current baseline period. The distribution of water resources in the river basin would become much more challenging in the future due to increased irrigation, domestic, hydropower, industrial and commercial, livestock, recreational, institute, and business use, multiple water uses, high population growth, and rapid economic

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development. The combined effects of the decreasing water supply and the increasing water demand would be detrimental to the production of hydropower and irrigation in the river basin.

Results from the study show how important it will be to create sustainable water management going forward to lessen the effects of climate change. However, this study did not take into account variations in land use. There will be more uncertainty as a result of the potential for upcoming events to change. Changes in the basin are predicted to include an increase in temperature rates, a decrease in precipitation totals and distribution, and a decrease in streamflow magnitudes. This study also emphasizes how critical it is to create long-term water resource management in response to potential climate change effects in the future. It is essential to take this action to ensure that there will always be enough water to meet future demands for irrigation and hydropower generation.

Numerous management techniques, including fundamental water supply management and methods for reducing water demand during drought seasons and times, have been developed to address these issues with water scarcity and adapt to changing climates (Salinas et al., 2016). Woodroffe et al. (1996) state that the basin's irrigation efficiency is currently less than 45%, which is insufficient for the effective use of irrigation water. Therefore, increasing irrigation effectiveness in the Omo-Gibe River basin is crucial. Water efficiency improvements could allow irrigation systems to save a significant amount of water. It is possible to conserve water by managing farm recovery, altering the farming operation's planting strategy, and implementing new irrigation techniques (such as drip and sprinkler irrigation). Utilizing strategies that improve water demand management, such as capacity management and water-saving techniques, water use could be gradually brought back to normal

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The distribution of surface water in the basin, which has a number of potential water sources, including groundwater and wastewater, as well as the potential use of water in the basin, are highlighted by the projections and quantification results of this study. From the perspective of managing the water supply, using springs more frequently and varying the current sources of water may help to reduce the amount of water available and the severity of extremely low water levels. Most experts concur that implementing just one adaptation strategy won't be enough to completely reverse or halt further increases in the stress on water availability. Therefore, the best course of action for managing water resources in a climate-resilient way would be to combine a number of strategies (such as water allocation, water supply management, and water demand management), along with IWRM, stakeholder engagement, and public awareness development levels.

5.2 Recommendations

Because of climate change, the water cycle is more unpredictable, which threatens sustainable development at the national and river basin levels. Climate change also leads to extreme weather events, makes it harder to predict when water will be available for different uses, changes the amount of water available, and reduces its quantity. Hydropower generation, irrigation, and other water-related industries are more necessary due to the rising water demand, and as a result, peatlands and other important water-dependent carbon sinks have suffered. To ensure, sustain and reduce climate change impacts on future water availability for irrigation and hydropower generation the following recommendations were identified.

- ❖ At the national regional and river basin levels, climate planning and policy must be taken into account in both the management of water resources and climate change.

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- The implementation of protected area systems, reforestation and afforestation initiatives, renewable energy and energy efficiency programs, ecological agriculture, adaptable livestock production, home gardens, conventional agroforestry systems, the collection and use/marketing of non-timber forest products, and climate change education should all be included in climate change planning and policy.
- More research should be done to assess the level of uncertainty surrounding future water availability and demand as a result of changes in infrastructure, land use, and technology.
- The catchment could have an impact on the future availability of water for irrigation, rain-fed agriculture, hydroelectric power generation, and other sectors if it does not put effective adaptation measures in place.
- Recommend that, to lessen this basin's exposure to the impacts of climate change going forward, practical and appropriate adaptation strategies and actions be put into place as soon as possible.
- Further research is required to determine whether these climate change adaptation options are appropriate for the Omo-Gibe River basin's potential impacts and climate change scenarios.
- It is important to conduct further research in the basin in order to determine the level of uncertainty in this basin future water supply (availability) and demand due to changes in infrastructure, land use, and technology.

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APPENDIXES

APPENDIX 1: Published Article form the Work

Appendices 1a: Orkodjo TP, Kranjac-Berisavijevic G, Abagale FK. Impact of climate change on future precipitation amounts, seasonal distribution, and streamflow in the Omo-Gibe basin, Ethiopia. Heliyon. 2022 Jun 15;8(6): e09711. https://doi.org/10.1016/j.heliyon. 2022.e09711

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APPENDIX 2: Streamflow Parameters Description Names, Fitted Value, and Allowable Range, for Calibration and Uncertainty Analysis

Streamflow parameters change method, description, and names	Allowable range	Fitted Value[a]	Fitted Vallue[b]
1: R__ Maximum canopy storage (CANMX.hru)	0-10	0.127	0.294
2: V__ Threshold depth of water in the shallow aquifer (GWQMN.gw)	0-5000	3186	3186.3
3: R__ Groundwater "revap" coefficient (REVAPMN.gw)	0-500	131.1	132.4
4: R__ SCS runoff curve number (CN2.mgt)	35-98	85.8	86.3
5: V__ Base flow alpha factor (ALPHA_BF.gw)	0-1	0.7	1.0
6: V__ Groundwater delay (GW_DELAY.gw)	30-450	411	413.0
7: R__ Soil evaporation compensation factor (ESCO.hru)	0-1	0.5	0.9

8: R__Effective hydraulic conductivity in main channel alluvium (CH_K2.rte)	0-1	0.6	0.8
9: R__ Groundwater "revap" coefficient (GW_REVAP.gw)	0.02-0.2	0.01	0.1
10: R__ Depth from the soil surface to bottom of layer (SOL_Z.sol)	0-3000	1441	1441.2
11: R__ saturated hydraulic conductivity (SOL_K(..).sol)	0-100	49	84.12
12: R__ Available water capacity of the soil layer (SOL_AWC(..).sol)	0-1	0.3	0.6
13: R__ Initial groundwater height (GWHT.gw)	0-25	10.0	11.5
14: R__ Fraction of porosity anions are removed ANION_EXCL.sol	0-1	0.6	0.8
15: R__ Deep aquifer percolation fraction (RCHRG_DP.gw)	0-1	0.3	0.6
16: R__ Manning's "n" value for the main channel (CH_N2.rte)	0-1	0.7	0.9
17: R__ Plant uptake compensation factor (EPCO.hru)	0-1	0.2	0.5
18: R__ Initial depth of water in the deep aquifer (DEEPST.gw)	0-50000	2998	3000
19: R__ Deep aquifer percolation fraction (RCHRG_DP.gw)	0-1	0.4	0.7
20: R__Maximum rooting depth of soil profile (SOL_ZMX.sol)	0-3500	229.0	583
21: R_Moist bulk density (SOL_BD.sol)	0.9-2.9	2.0	1.7

V__ means the existing parameter value is to be replaced by a given value and R__ means an existing parameter value is multiplied by (1+ a given value) Source: Neitsch et al. (2011).

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APPENDIXE 3: Observed Rainfall Data

Month	Assandabo	Bako	Jimma	Lemugenet	sekeru	shebe	Wolikite	Wosha	sawula	Jinka	Hossana	Woliso	Wolata sodo	Ejeje
January	616.1	791.1	900.2	704.7	356.0	1520.8	591.2	494.5	1091.3	1005.8	731.3	1307.2	1273.2	749.5
February	513.0	659.0	814.7	584.8	455.8	2252.3	757.4	633.1	1620.0	1493.1	611.0	1892	1890	741.8
March	1626.9	2023.6	2469.9	1799.8	1083.2	2205.3	1786.2	1504.5	1584.9	1460.7	1965.8	1865	1849	1751.1
April	2089.8	3052.0	3618.5	2718.3	1576.2	4253.5	2626.6	2189.1	3056.0	2816.6	2488.1	3567.3	3518.3	2548.7
May	3527.3	3467.5	3973.8	3127.3	2404.8	7259.6	3865.4	3340	5284.8	4870.7	4208.8	6150.5	6169.5	4153.1
June	5312.3	5076.2	6174.8	4518.2	4027.2	8269.7	6424.1	5593.4	5984.6	5515.8	6376.4	6940	6964	6353.1
July	6612.8	4832.1	5943.0	4295.3	6024.9	8279.8	9498.7	8367.9	6010.4	5539.6	7868.1	7018.1	6926.1	7882.2
August	6629.7	5427.7	6566.7	4831.3	5694.3	5164.3	9067.0	7908.8	3695.0	3442.4	7864.8	4288.5	4357.5	7888.9
September	4388.8	4933.5	6047.4	4386.7	3246.3	2319.4	5030.4	4508.8	1682.8	1551.0	5205.7	1963.3	1885.3	4890.1
October	1904.6	2028.3	2471.9	1818.8	1002.6	805.0	1596.0	1362.5	578.7	533.4	2307.3	675.2	615.2	1958.73
November	654.1	1753.7	2017.4	1569.9	262.3	714.8	493.3	364.3	516.2	475.7	770.9	602.2	562.2	692.8
December	321.6	825.5	1045.2	734.6	130.5	671.6	215.1	181.2	482.7	444.9	384.3	563.2	560.2	377

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APPENDIXE 3a: Monthly Total Observed Rainfall Data (1987-2019)

Month	Assandabo	Bako	Jimma	Lemugenet	sekeru	shebe	Wolikite	Wosha	sawula	Jinka	Hossana	Woliso	Wolata sodo	Ejeje
January	616.1	791.1	900.2	704.7	356.0	1520.8	591.2	494.5	1091.3	1005.8	731.3	1307.2	1273.2	749.5
February	513.0	659.0	814.7	584.8	455.8	2252.3	757.4	633.1	1620.0	1493.1	611.0	1892	1890	741.8
March	1626.9	2023.6	2469.9	1799.8	1083.2	2205.3	1786.2	1504.5	1584.9	1460.7	1965.8	1865	1849	1751.1
April	2089.8	3052.0	3618.5	2718.3	1576.2	4253.5	2626.6	2189.1	3056.0	2816.6	2488.1	3567.3	3518.3	2548.7
May	3527.3	3467.5	3973.8	3127.3	2404.8	7259.6	3865.4	3340	5284.8	4870.7	4208.8	6150.5	6169.5	4153.1
June	5312.3	5076.2	6174.8	4518.2	4027.2	8269.7	6424.1	5593.4	5984.6	5515.8	6376.4	6940	6964	6353.1
July	6612.8	4832.1	5943.0	4295.3	6024.9	8279.8	9498.7	8367.9	6010.4	5539.6	7868.1	7018.1	6926.1	7882.2
August	6629.7	5427.7	6566.7	4831.3	5694.3	5164.3	9067.0	7908.8	3695.0	3442.4	7864.8	4288.5	4357.5	7888.9
September	4388.8	4933.5	6047.4	4386.7	3246.3	2319.4	5030.4	4508.8	1682.8	1551.0	5205.7	1963.3	1885.3	4890.1
October	1904.6	2028.3	2471.9	1818.8	1002.6	805.0	1596.0	1362.5	578.7	533.4	2307.3	675.2	615.2	1958.73
November	654.1	1753.7	2017.4	1569.9	262.3	714.8	493.3	364.3	516.2	475.7	770.9	602.2	562.2	692.8
December	321.6	825.5	1045.2	734.6	130.5	671.6	215.1	181.2	482.7	444.9	384.3	563.2	560.2	377

APPENDIXE 4: Observed average Minimum temperature

APPENDIXE 4a: Observed average Minimum temperature (1987-2019)

Month	Assandabo	Backo	Jimma	Lmgttmp	Skrutmp	Shebtmp	Wlkttmp	Wlsotmp	Swultmp	Jnkatmp
January	11.2	12.0	10.1	12.7	11.7	11.9	12.0	12.6	13.1	12.7
February	12.1	13.2	12.1	13.6	12.8	12.7	12.9	13.5	14.0	13.1
March	14.3	14.0	13.2	14.4	13.7	13.6	15.0	14.1	14.6	13.7
April	14.8	14.3	14.4	15.0	14.3	14.2	15.4	14.6	15.1	14.0
May	15.1	14.6	14.8	14.8	14.9	14.1	15.6	14.5	15.0	14.0
June	14.2	14.5	15.1	14.2	14.2	13.4	15.0	14.0	14.5	13.4
July	14.3	14.3	15.0	14.3	14.1	13.4	15.1	14.1	14.6	12.9
August	14.1	14.3	15.1	14.3	14.1	13.5	15.0	14.1	14.6	13.4
September	13.7	14.0	14.8	14.0	14.0	13.2	14.5	13.9	14.4	13.8
October	12.6	12.9	12.6	13.0	13.1	12.3	13.2	12.8	13.3	13.7
November	10.5	11.8	10.7	12.2	12.0	11.2	11.5	11.8	12.3	12.8
December	10.0	11.4	9.2	12.0	11.1	11.0	11.1	11.2	11.7	12.4

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APPENDIXE 4b: Observed Maxmum Temperature (1987-2019)

Month	Assandabo	Backo	Jimma	Lmgttmp	Skrutmp	Shebtmp	Wlkttmp	Wlsotmp	Swultmp	Jnkatmp
January	29.2	30.2		28.5	27.7	29.4	29.4	28.0	29.9	28.3
February	30.1	31.2	30.3	30.1	28.6	29.9	30.1	29.2	30.5	29.2
March	30.2	31.3	30.3	29.7	28.7	29.8	30.5	29.4	30.2	29.0
April	29.0	30.9	29.2	29.0	28.1	28.7	30.1	28.7	28.9	27.8
May	28.4	29.2	28.4	27.9	27.6	27.8	28.8	28.1	28.7	26.8
June	26.7	26.7	27.0	25.9	24.4	26.5	27.1	25.0	28.6	26.8
July	24.8	25.1	25.3	24.1	23.2	25.4	25.5	22.9	27.2	26.6
August	24.9	24.3	25.3	24.6	23.3	25.4	24.7	23.0	27.6	27.0
September	26.1	25.5	25.6	25.7	24.1	25.7	26.2	24.6	28.3	28.1
October	27.4	27.9	27.4	26.3	25.5	27.1	28.9	26.7	28.7	27.7
November	28.3	29.0	27.9	27.2	26.4	27.7	29.7	27.2	29.0	27.4
December	28.5	30.0	28.3	28.0	26.9	27.8	29.1	27.3	29.0	27.9

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APPENDIXE 5: Projected Max Temperature

APPENDIXE 5a: Projected Max Temperature RCMs_RCP_4.5 (2017-244)

Month	CNRM-CERFACS-CM5-SMHI_RCA4	ICHEC-EC-EARTH_DMI_HIRHAM5	_ICHEC-EC-EARTH_KNMI_RACM022	ICHEC-EC-EARTH_SMHI-RAC4	MPI-M-MPI-ESM-LR_SMHI_RCA4	MPI-M-MPI-ESM-LR_UQAM_CRCM	AFR-44_NOAA-GFDL-GFDL-ESM2M_SMHI	CCCma-CanESM2_CCCma-CanRCM4	MIROC-MIROC5_SMHI_RAC4	CCCma-CanESM2_SMHI	NCC-NorESM1-M_SMHI_RCA4
January	25.3	25.4	25.9	25.8	25.9	26.3	36.8	37.5	37.7	37.4	26.0
February	26.4	26.0	26.8	26.8	26.6	26.9	37.7	36.5	38.0	37.3	26.7
March	26.9	26.7	27.5	27.3	27.0	27.7	37.4	36.7	38.0	37.7	26.8
April	26.1	26.6	26.7	26.7	27.1	27.4	36.7	35.6	36.4	36.8	26.3
May	25.4	25.1	25.9	25.6	26.3	26.0	34.7	34.7	34.9	35.8	24.0
June	23.4	23.3	22.9	23.9	24.2	25.0	33.1	32.5	32.8	33.4	21.6
July	21.4	21.8	21.4	21.6	22.2	22.4	32.8	32.2	31.7	32.4	20.9
August	21.2	21.7	21.3	21.7	21.6	21.7	33.2	32.7	32.4	32.6	21.4
September	21.9	22.3	22.2	22.6	22.1	22.3	34.2	33.2	34.2	34.1	23.4
October	23.7	23.7	23.9	24.0	24.1	24.2	34.7	34.9	35.6	35.4	24.7

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November	24.2	24.2	24.4	24.9	24.9	25.0	35.2	35.7	36.5	36.0	24.6
December	24.4	24.6	24.9	25.3	25.2	25.6	35.5	35.9	36.6	36.5	25.2

APPENDIXE 5b: Projected Minimum Temperature RCMs_RCP_8.5 (2017-244)

Month	CNRM-CERFACS-CM5-SMHI_RCA4	ICHEC-EC-EARTH_DMI_HIRHAM5	ICHEC-EC-EARTH_KNMI_RACM022	ICHEC-EC-EARTH_SMHI-RAC4	MPI-M-MPI-ESM-LR_SMHI_RCA4	MPI-M-MPI-ESM-LR_UQAM_CRCM	
January	9.8	9.6	10.2	10.6	10.4	10.2	10.1
February	11.5	11.4	12.2	12.3	12.2	11.9	11.9
March	12.5	12.5	13.1	13.6	13.1	12.9	12.9
April	13.2	13.0	13.4	13.5	14.1	13.7	13.5
May	13.2	12.4	13.1	13.4	14.4	13.3	13.3
June	12.3	11.6	12.2	12.2	12.5	12.8	12.3
July	11.8	11.9	12.4	11.8	11.9	12.5	12.1
August	12.2	12.0	12.8	12.2	12.2	12.5	12.3
September	11.8	11.2	11.9	11.6	12.0	11.9	11.8
October	11.2	10.5	11.2	11.6	11.7	11.1	11.2
November	9.9	9.5	10.2	10.2	10.6	10.2	10.1
December	9.3	9.2	9.6	10.2	9.7	9.1	9.5

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APPENDIXE 5c: Projected Min Temperature RCMs_RCP_4.5 (2045-2072)

Month	CNRM-CERFACS-CM5-SMHI_RCA4	ICHEC-EC-EARTH_DMI_HIRHAM5	ICHEC-EC-EARTH_KNMI_RACM022	ICHEC-EC-EARTH_SMHI-RAC4	MPI-M-MPI-ESM-LR_SMHI_RCA4
January	10.7	10.0	10.7	10.6	11.2
February	12.0	11.5	12.1	12.0	12.2
March	13.6	12.7	13.4	13.5	13.1
April	14.0	13.2	13.9	13.6	14.2
May	13.8	13.2	13.6	13.7	14.0
June	14.0	13.1	13.1	13.2	13.8
July	14.7	13.7	13.3	13.8	13.9
August	14.3	13.3	13.2	13.3	13.4
September	13.6	12.5	12.4	12.6	12.9
October	11.9	11.2	11.0	11.7	12.1
November	10.3	10.4	10.4	10.1	10.6
December	9.6	9.7	9.8	9.6	10.1

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APPENDIXE 5d: Projected Min Temperature RCMs_RCP_8.5 (2045-2072)

Month	CNRM-CERFACS-CM5-SMHI_RCA4	ICHEC-EC-EARTH_DMI_HIRHAM5	ICHEC-EC-EARTH_KNMI_RACM022		MPI-M-MPI-ESM-LR_SMHI_RCA4
January	27.6	27.7	27.5	27.8	28.0
February	28.0	28.5	28.7	28.6	28.9
March	28.2	28.6	28.4	28.7	29.8
April	28.0	28.1	28.9	28.4	29.9
May	26.6	27.1	27.5	26.9	28.5
June	24.7	25.3	24.4	25.3	26.8
July	23.0	23.9	23.1	23.7	24.5
August	22.7	23.8	22.7	23.2	23.3
September	23.3	23.9	23.7	24.3	23.7
October	24.7	25.7	25.2	25.3	25.6
November	26.0	26.5	25.9	26.0	26.4
December	26.8	27.1	26.6	26.6	27.0

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APPENDIXE 5e: Projected Minimum Temperature RCMs_RCP_5.5 (2045-2072)

Month	CNRM-CERFACS-CM5-SMHI_RCA4	ICHEC-EC-EARTH_DMI_HIRHAM5	ICHEC-EC-EARTH_KNMI_RACM022	ICHEC-EC-EARTH_SMHI-RAC4	MPI-M-MPI-ESM-LR_SMHI_RCA4	MPI-M-MPI-ESM-LR_UQAM_CRCM	
January	11.0	10.4	11	11.0	11.0	12.1	6.1
February	12.5	12.0	13	12.6	12.1	13.4	7.4
March	14.0	13.1	14	13.7	13.5	14.9	8.9
April	14.5	13.6	14	13.8	14.2	15.0	9.0
May	14.5	13.8	14	13.7	14.0	14.2	8.2
June	14.4	13.6	14	13.6	13.9	13.8	7.8
July	15.0	14.2	14	14.4	14.1	12.4	6.4
August	14.7	13.7	13	13.9	13.6	11.3	5.3
September	13.8	12.9	13	13.0	13.0	11.3	5.3
October	12.2	11.7	11	12.2	11.9	11.8	5.8
November	10.5	10.8	11	10.6	10.8	11.6	5.6
December	10.0	9.8	10	9.8	10.3	11.4	5.4

APPENDIXE 4f: Projected Munmun Temperature RCMs_RCP_8.5 (2073-2100)

Month	CNRM-CERFACS-CM5-SMHI_RCA4	ICHEC-EC-EARTH_DMI_HIRHAM5	ICHEC-EC-EARTH_KNMI_RACM022	ICHEC-EC-EARTH_SMHI-RAC4	MPI-M-MPI-ESM-LR_SMHI_RCA4	MPI-M-MPI-ESM-LR_UQAM_CRCM
January	27.1	27.4	26.8	27.6	27.1	26.9
February	28.1	27.9	27.3	28.2	28.2	28.5
March	28.0	28.1	27.7	28.4	28.4	29.1
April	27.8	27.8	27.3	27.7	28.5	28.7
May	26.4	26.5	26.5	26.7	27.1	27.3
June	25.0	25.1	24.3	25.2	25.4	25.8
July	22.1	23.6	22.6	23.1	23.5	23.2
August	22.1	22.8	22.4	23.1	22.5	22.5
September	23.0	23.3	23.3	23.5	23.0	23.2
October	24.6	25.4	24.8	25.1	24.4	24.8
November	25.5	25.9	25.4	25.7	25.4	25.6
December	26.1	26.4	26.0	26.2	26.0	25.8

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APPENDIXE 6: Projected precipitation

APPENDIXE 6a: Monthly Total Projected Precipitation under RCP_4.5 (2017-2044)

Month	CNRM-CERFACS-CNRM-SMHI-RCM4	ICHEC-EC-EARTH_DMI_HIRHAM5	ICHEC-EC-EARTH_KNMI_RACM022	ICHEC-EC-EARTH_SMHI-RAC4	MPI-M-MPI-ESM-LR_SMHI_RCA4	MPI-M-MPI-ESM-LR_UQAM_CRCM	CCCma-canESM2-RCP45	CCMA-canRCM4	NOAA-GFDL-GFDL-ESM_SMHI_RCA4	MIROC-MIROC5_SMHI_RAC4
January	748.3049	454.9243	138.8184	157.023	335.1645	19.4621	633.7201	281.0023	308.2931	167.7532
February	1269.114	1551.2902	455.0863	484.4127	496.3988	207.8373	2089.399	149.5805	873.7815	513.7697
March	1362.866	1160.22	1311.101	1175.128	1074.445	393.5434	2097.356	1588.849	1231.564	883.3029
April	1543.52	2004.977	1563.319	1606.743	1351.813	771.1869	2747.747	1917.882	3103.002	1907.196
May	3122.767	2268.404	2446.418	2035.635	2868.375	1522.383	4196.357	3063.667	2631.988	2650.709

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June	4800.904336.2312	4382.929	4085.808	3458.86	4997.677	6221.229	4126.687	4855.197	6036.426
July	6917.634883.4467	8412.35	8054.427	7316.329	8506.379	9923.477	3985.523	5829.554	5770.716
August	6445.475853.1065	7433.207	6883.876	8496.858	4710.328	6087.413	2564.749	4090.608	4818.042
September	4247.243174.5533	3172.817	4190.599	4211.201	970.9266	3086.101	1698.755	1601.993	565.2883
October	1608.091221.9496	991.3967	1204.687	1394.473	267.9043	727.9545	605.6656	301.5717	339.0498
November	726.763486.31668	243.7705	182.7607	197.5409	168.5012	112.8706	282.8983	66.87028	231.1751
December	677.536295.00039	224.3724	233.4209	282.1802	36.43794	475.1516	149.2053	257.8352	62.78614

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APPENDIXE 6b: Monthly Total Projected Precipitation under RCP_8.5 (2017-2044)

Month	CNRM-CERFACS-CM5-SMHI_RCA4	ICHEC-EC-EARTH_DMI_HIRHAM5	ICHEC-EC-EARTH_KNMI_RACM022	ICHEC-EC-EARTH_SMHI-RAC4	MPI-M-MPI-ESM-LR_SMHI_RCA4	MPI-M-MPI-ESM-LR_UQAM_CRCM	CCCma-canESM2-SMHI-RCA4-	CCMA-canRCM4	NOAA-GFDL-GFDL-ESM_SMHI_RCA4	MIROC-MIROC5_SMHI_RAC4
January	725.88	676.11	432.47	116.98	54.89	69.80	87.94	522.82	136.03	490.01
February	588.17	1459.24	1023.02	460.51	287.59	289.12	64.36	1475.11	417.68	1289.10
March	1600.95	1085.06	1507.79	1578.84	1211.50	1702.66	274.86	1979.67	1352.06	1087.80
April	1333.74	1201.78	1308.12	1648.61	1021.86	1541.55	595.16	2428.54	1898.42	2389.71
May	3206.30	3201.69	2707.21	2579.89	1761.37	2390.51	2634.41	3684.20	2900.23	2710.46
June	5005.27	4017.85	4963.36	4717.72	3319.88	4232.47	5015.67	3694.74	4834.65	4902.38
July	6095.12	7320.88	5876.76	8125.83	5498.73	7288.07	8217.53	9705.58	4005.47	7378.48
August	4293.70	6931.76	6570.51	7059.54	6574.43	7026.08	4775.26	7584.30	2610.57	3976.36
September	1482.97	3740.24	4286.57	2825.40	3413.77	3083.71	715.44	2110.02	1707.95	1462.67

October	230.14	932.70	1122.23	1152.44	1846.03	1238.24	372.92	1277.01	264.18	299.77
November	267.12	958.05	466.42	380.61	182.97	344.34	262.30	186.01	378.12	280.58
December	267.12	665.59	307.90	466.51	175.63	376.11	211.72	497.51	373.23	326.49

APPENDIXE 6c: Monthly Total Projected Precipitation under RCP_4.5 (2045-2072)

Month	**CNRM-CERFACS-CNRM-SMHI-RCM4**	**ICHEC-EC-EARTH_DMI_HIRHAM5**	**ICHEC-EC-EARTH_KNMI_RACM022**	**ICHEC-EC-EARTH_SMHI-RAC4**	**MPI-M-MPI-ESM-LR_SMHI_RCA4**	**MPI-M-MPI-ESM-LR_UQAM_CRCM**	**CCCma-canESM2-**	**CCMA-canRCM4**	**CCMA-canRCM4**	**NOAA-GFDL-GFDL-ESM_SMHI_RCA4**	**MIROC-MIROC5_SMHI_RAC4**

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January	182.18	612.54	563.44	261.99	90.92	363.28	1.96	368.81	119.13	556.33	353.67
February	522.43	1392.35	826.32	364.10	177.88	378.83	81.93	1632.21	423.64	716.26	486.99
March	1448.83	1110.61	1412.55	1616.86	551.99	814.79	585.84	1997.54	1903.61	1506.44	1541.10
April	1302.19	1898.11	1054.75	1486.69	1443.57	1610.24	658.30	2635.15	2228.69	3396.40	1767.98
May	2423.40	3018.12	2404.47	1785.19	1408.10	1968.59	2436.47	4307.29	3109.40	3732.72	3348.00
June	3188.08	4206.22	4249.76	3440.71	2675.43	2896.43	4722.00	6383.29	3009.56	4780.15	6028.83
July	5667.78	7052.02	5057.69	6852.72	5618.62	8587.04	8390.04	7667.16	3730.11	5266.42	5855.41
August	6774.42	7389.56	6346.75	6773.24	6681.67	9435.32	3679.16	5930.06	2391.26	3736.97	4389.77
September	4444.06	4339.53	3211.78	3611.48	4370.08	5041.63	496.51	1752.27	1462.06	1106.34	506.54
October	1014.71	1167.83	902.85	1212.25	1763.40	2143.12	399.64	825.27	416.68	108.92	433.45
November	273.50	904.85	329.76	366.57	333.87	406.23	190.02	129.56	266.92	58.95	179.17

December	344.59	638.94	260.09	354.58	334.32	278.09	17.64	604.73	160.59	357.46	83.55

APPENDIXE 6d: Monthly Total Projected Precipitation under RCP_8.5 (2045-2072)

Month	CNRM-CERFACS-CNRM-SMHI-RCM4	ICHEC-EC-EARTH_DMI_HIRHAM5	ICHEC-EC-EARTH_KNMI_RACM022	ICHEC-EC-EARTH_SMHI-RAC4	MPI-M-MPI-ESM-LR_SMHI_RCA4	MPI-M-MPI-ESM-LR_UQAM_CRCM	CCCma-canESM2-RCP45	CCMA-canRCM4	CCMA-canRCM4	NOAA-GFDL-GFDL-ESM_SMHI_RCA4	MIROC-MIROC5_SMHI_RAC4
January	151.6	657.0	545.5	260.4	151.7	151.7	226.1	1074.1	192.3	390.1	162.2
February	1152.6	998.8	351.9	624.0	207.9	207.9	188.6	2180.2	330.8	1092.1	886.7
March	649.8	1368.0	1469.3	1564.2	549.4	549.4	435.9	1836.8	2119.3	1569.2	1161.9
April	1531.7	1416.3	969.9	1524.7	945.8	945.8	978.5	2740.7	2247.9	2324.0	1921.7
May	1099.4	2343.0	2299.0	2399.0	1417.5	1417.5	3608.5	3609.7	2486.6	3050.7	3101.8
June	2466.6	4259.6	5478.8	3470.9	2766.2	2766.2	3880.2	6661.9	2261.9	4270.4	4791.8
July	4527.6	7450.2	5084.3	8064.0	6493.0	6493.0	6981.5	8095.5	3295.5	4870.2	6507.1

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August	5479.3	7788.0	5957.4	8326.0	6247.5	6247.5	4573.1	7615.6	1613.7	3273.2	4425.4
September	4305.9	4161.1	3369.3	2202.0	3744.4	3744.4	614.5	1902.6	1279.5	1668.3	637.7
October	1508.1	1425.8	1362.1	1512.1	1270.3	1270.3	130.7	801.8	309.4	131.5	383.8
November	224.4	753.5	833.4	346.5	376.5	376.5	198.7	191.3	328.9	68.6	293.8
December	116.7	598.1	300.5	249.4	92.3	92.3	28.0	697.4	53.9	334.1	100.9

APPENDIXE 6e: Monthly Total Projected Precipitation under RCP_4.5 (2073-2100)

Month	CNRM-CERFACS-CNRM-SMHI	ICHEC-EC-EARTH_DMI_HIRHAM5	ICHEC-EC-EARTH_KNMI_RACM022	ICHEC-EC-EARTH_SMHI-RAC4	MPI-M-MPI-ESM-LR_SMHI_RCA4	MPI-M-MPI-ESM-LR_UQAM CRCM	CCCma-canESM2-RCP45	CCMA-canRCM4	NOAA-GFDL-GFDL-ESM_SMHI_RCA4	MIROC-MIROC5_SMHI_RAC4	NCC-NorESM1-M_SMHI_RCA4

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RCM4

January	286.905	828.2597	763.5526	82.62138	139.7981	337.7039	229.4257	816.7117	255.431	482.8926	72.54091
February	639.5299	1224.93	819.9578	499.8373	103.4967	215.1126	503.4718	2346.22	557.5623	957.4488	664.674
March	1363.892	1115.804	1290.954	1493.703	1059.479	706.9932	787.9746	2263.75	2419.612	1484.797	1313.406
April	1461.086	1240.416	2005.066	1465.106	1093.958	1200.446	713.0242	2675.844	1863.956	2006.525	1345.134
May	2175.485	2923.649	2132.177	1939.239	1972.719	2266.067	3478.521	4363.887	3001.804	3048.899	4049.004
June	2912.782	3723.621	4816.707	2990.089	3505.369	2985.383	4620.866	7714.843	3216.489	5071.038	5221.795
July	7237.779	5862.864	5306.231	6562.065	5397.936	8694.353	6269.413	8320.9	2616.878	5044.527	5893.369
August	8120.888	7380.605	5309.183	7308.219	6406.233	7769.79	2453.051	6253.41	1633.774	2379.596	3363.156
September	3577.839	3838.276	3173.384	2316.937	3496.771	4266.49	601.9147	1487.33	953.738	667.6519	492.1797
October	1507.582	1174.7	988.4516	1196.348	1696.379	1728.408	378.1231	426.5789	332.5196	116.8421	244.6904
November	180.2139	958.7455	713.9186	384.5043	299.1593	327.3642	57.49598	246.2539	197.6606	173.5923	140.191

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December	193.7699	673.4786	276.3457	286.4445	236.5854	314.4644	37.62823	744.2796	228.7725	477.6926	63.72497

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APPENDIXE 6f: Monthly Total Projected Precipitation under RCP_8.5 (2073-2100).

Month	CNRM-CERFACS-CM5-SMHI_RCA4	ICHEC-EC-EARTH_DMI_HIRHAM5	ICHEC-EC-EARTH_KNMI_RACM022	ICHEC-EC-EARTH_SMHI-RAC4	MPI-M-MPI-ESM-LR_SMHI_RCA4	MPI-M-MPI-ESM-LR_UQAM_CRCM	CCCma-canESM2-SMHI-RCA4-RCP85	CCMA-canRCM4	NOAA-GFDL-GFDL-ESM_SMHI_RCA4	MIROC-MIROC5_SMHI_RAC4	NCC-NorESM1-M_SMHI_RCA4
January	351.2739	894.1966	701.339	223.5564	126.1863	126.1863	168.6179	1416.024	129.0763	692.6338	160.5017
February	699.0095	1263.386	359.8288	510.9543	122.3262	122.3262	369.9372	2966.656	271.7916	977.9015	456.2397
March	294.1123	982.1267	1100.474	819.3024	682.7598	682.7598	825.5264	1752.459	1541.83	1061.883	1164.769
April	1565.912	1643.355	1244.486	1121.171	920.0343	920.0343	921.4264	3147.712	1366.308	2659.224	1119.677
May	919.8851	3238.614	2473.452	1947.698	944.4999	944.4999	2740.215	3380.933	2366.036	3130.464	2548.498
June	2220.845	4412.1	4998.885	2763.915	1511.878	1511.878	3468.502	6546.242	2986.593	6755.338	5835.829

July	5760.065	8938.193	5483.642	7339.446	4367.097	4367.097	5842.799	10016.1	2707.62	5773.178	5475.798
August	6320.381	6982.108	6806.283	5881.916	6764.278	6764.278	4015.301	6130.704	1510.47	3486.277	3377.103
September	5246.68	3833.062	3046.803	2787.824	2905.195	2905.195	263.5168	2416.905	956.0385	1647.648	433.4188
October	1243.953	1582.915	1261.499	1447.27	1656.192	1656.192	201.2606	810.9086	362.7231	88.59888	369.8217
November	472.6868	964.5077	1015.55	265.4863	297.5018	297.5018	177.8148	366.4082	289.8307	29.19845	179.7606
December	131.491	786.4239	227.7807	264.1193	380.7803	380.7803	206.163	1007.737	17.71524	341.3511	70.8603

APPENDIXE 7: Streamflow

APPENDIXE 7a: Observed Streamflow

Daily streamflow

Station Number: 061015 Year: 2006

Station Name: G. GIBE @ ABELTI (061015)

Area: 15746.0 sq km

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1	41.53	83.017	68.192	37.165	68.192	52.5	120.635	461.747	630.259	394.313	221.345	149.131
2	56.524	76.2	35.097	77.87	37.165	66.658	122.865	409.271	675.773	411.766	214.896	92.063
3	52.5	57.908	51.201	84.779	42.669	76.2	162.15	476.773	889.273	371.907	199.299	83.017

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4	49.921	46.205	52.5	63.654	45.007	59.312	251.874	399.297	607.538	364.447	162.15	84.779
5	66.658	41.53	39.309	62.185	39.309	69.749	167.552	459.244	587.362	361.961	146.609	74.554
6	95.849	39.309	40.41	68.192	38.228	77.87	175.866	537.011	589.883	361.961	134.406	86.565
7	46.205	62.185	34.091	71.328	45.007	77.87	214.896	784.852	688.432	352.023	129.711	63.654
8	33.103	90.207	40.41	51.201	42.669	77.87	290.106	640.365	653.004	344.575	125.121	72.93
9	36.122	72.93	52.5	60.738	59.312	81.278	51.201	723.912	607.538	344.575	134.406	59.312
10	40.41	68.192	47.424	63.654	41.53	76.2	136.793	769.604	630.259	349.54	118.431	57.908
11	38.228	72.93	39.309	55.162	66.658	105.74	251.874	948.011	610.061	334.652	93.944	69.749
12	53.821	77.87	29.333	69.749	48.662	88.374	221.345	772.145	592.404	327.215	120.635	77.87
13	92.063	65.145	21.873	105.74	49.921	105.74	269.924	663.121	549.586	322.26	120.635	69.749
14	74.554	97.778	55.162	93.944	38.228	90.207	266.251	761.983	572.243	295.046	107.792	68.192
15	56.524	74.554	68.192	92.063	48.662	125.121	255.421	1119.7	615.109	295.046	99.732	59.312
16	77.87	74.554	56.524	81.278	74.554	116.252	251.874	930.123	584.841	280.233	114.099	76.2
17	86.565	60.738	35.097	83.017	41.53	95.849	295.046	879.07	663.121	366.933	129.711	88.374
18	88.374	59.312	40.41	103.712	48.662	95.849	282.7	1076.06	579.801	277.367	103.712	65.145
19	60.738	30.248	52.5	109.869	43.828	86.565	307.407	953.124	529.47	273.63	244.873	81.278
20	59.312	47.424	77.87	51.201	31.182	141.648	285.168	1158.248	509.376	282.7	107.792	97.778
21	62.185	57.908	55.162	32.133	45.007	154.256	327.215	1073.494	461.747	241.42	107.792	72.93
22	79.562	56.524	95.849	81.278	26.692	164.837	307.407	1696.205	451.738	231.244	103.712	93.944
23	62.185	59.738	114.099	62.185	63.654	146.609	356.991	1191.686	434.237	218.105	95.849	71.328

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24	79.562	53.821	68.192	28.435	36.122	178.695	394.313	653.004	464.251	221.345	86.565	65.145
25	93.944	59.312	84.779	37.165	48.662	134.406	334.652	825.557	424.245	214.896	79.562	57.908
26	60.738	60.738	65.145	69.749	62.185	154.256	534.497	843.383	416.756	193.266	118.431	69.749
27	57.908	56.524	65.145	43.828	48.662	129.711	471.763	741.671	391.822	205.449	79.562	71.328
28	88.374	49.921	63.654	46.205	60.738	162.15	584.841	736.596	401.79	205.449	99.732	97.778
29	49.921	49.921	45.007	49.921	49.921	170.296	577.281	698.564	424.245	208.568	95.849	62.185
30	65.145	49.921	88.374	43.828	65.145	159.491	434.237	690.964	414.261	214.896	107.792	77.87
31	125.121	125.121	69.749	43.828	72.93	159.491	444.235	688.432	688.432	205.449	60.738	60.738
Mean	65.533	62.597	56.534	66.041	49.377	110.719	295.109	798.813	555.014	292.653	126.805	76.725
Flow (MCM)	175.523	151.435	151.421	171.178	132.252	286.983	790.42	2139.542	1438.597	783.841	328.678	205.499
Maximum	125.121	97.778	114.099	109.869	74.554	178.695	584.841	1696.205	889.273	411.766	244.873	149.131
Minimum	33.103	30.248	21.873	28.435	26.692	52.5	51.201	399.297	391.822	193.266	79.562	57.908
Runoff (mm)	11.147	9.617	9.616	10.871	8.399	18.226	50.198	135.878	91.363	49.78	20.874	13.051

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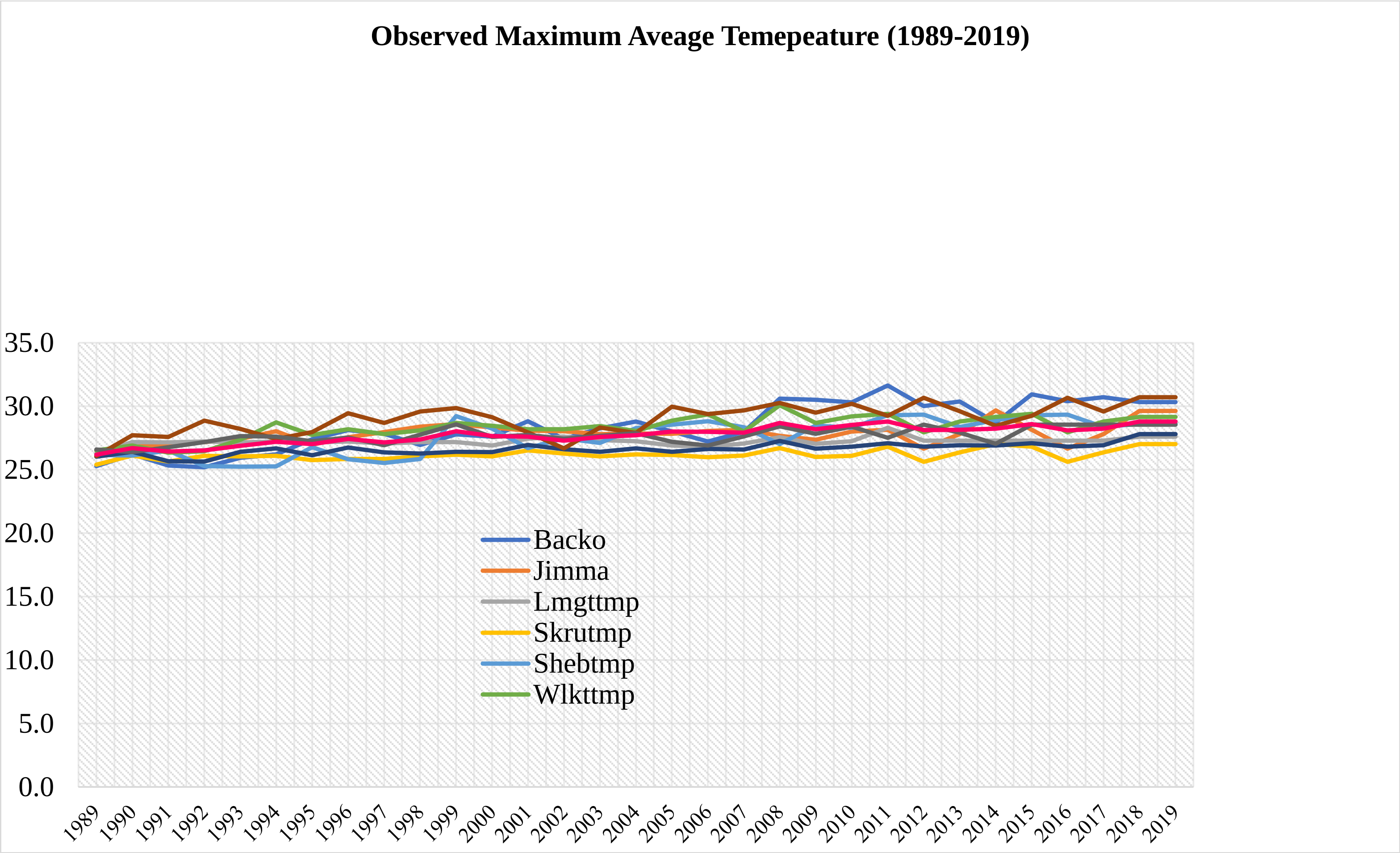
APPENDIXE 8: Observed Temperature and Precipitation graphs

APPENDIXE 8a: Observed annual Maximum Average Temperature



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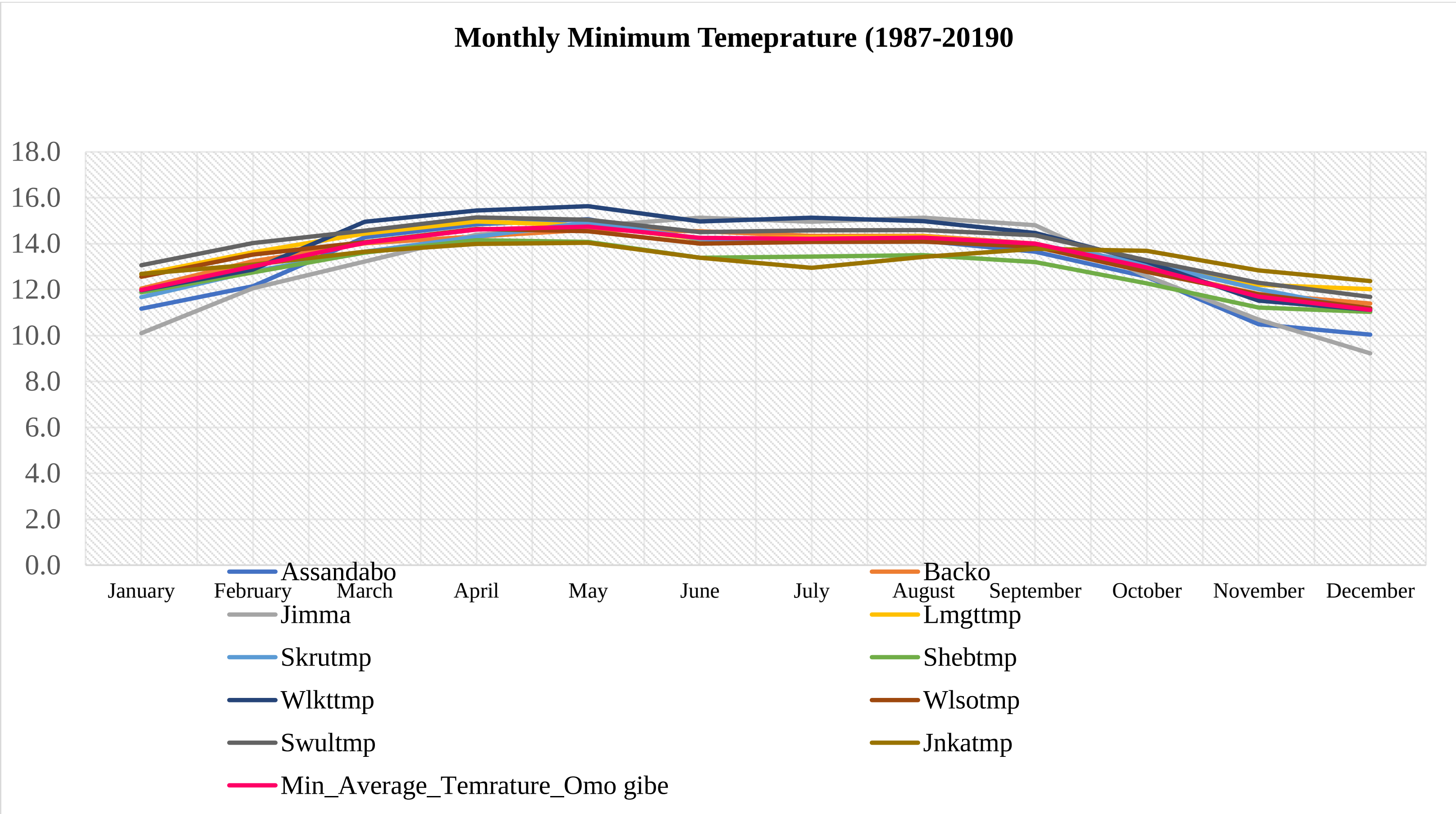
APPENDIX 8b: Observed Monthly Minimum Average Temperature



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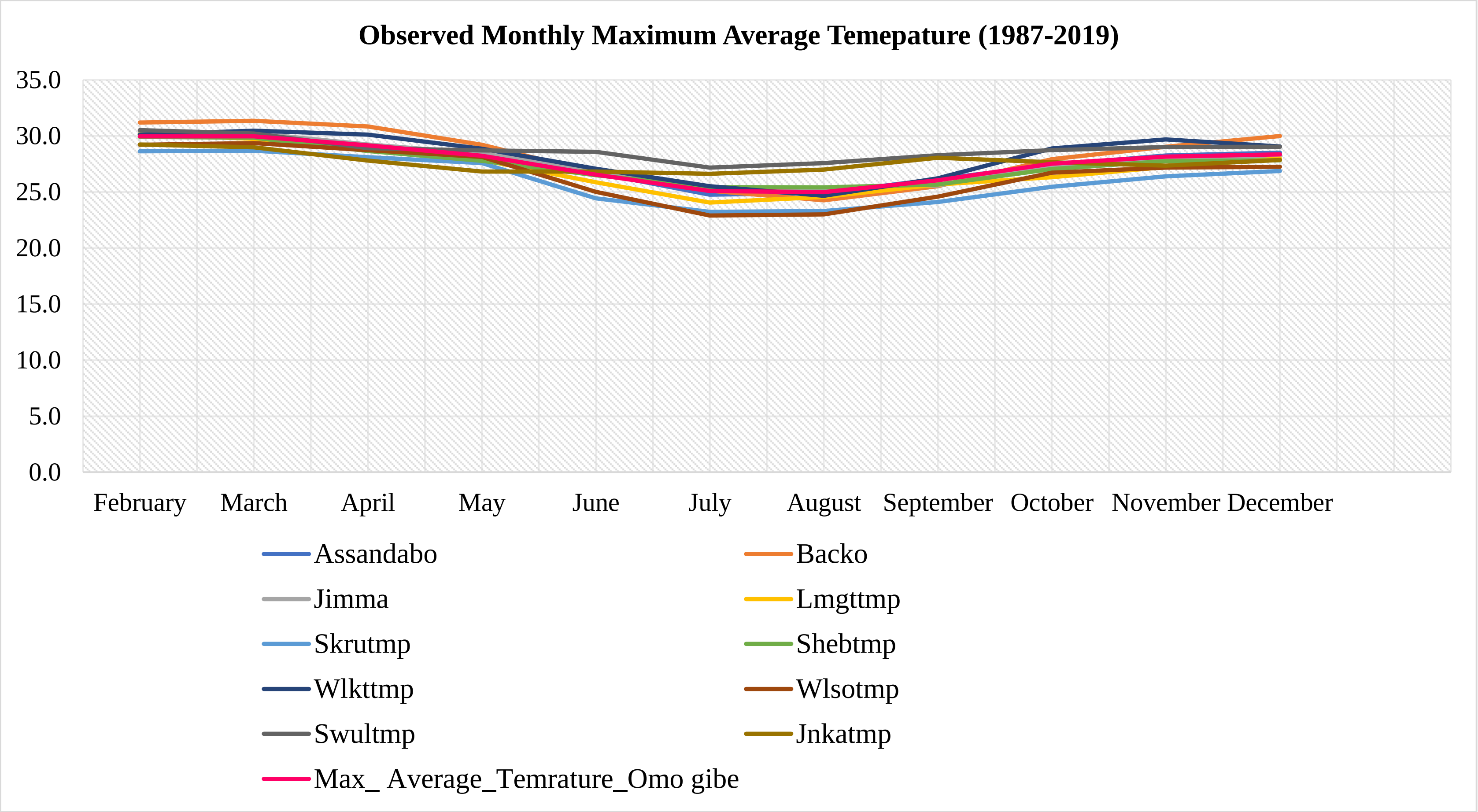
APPENDIX 8c: Observed Monthly Maximum Average Temperature



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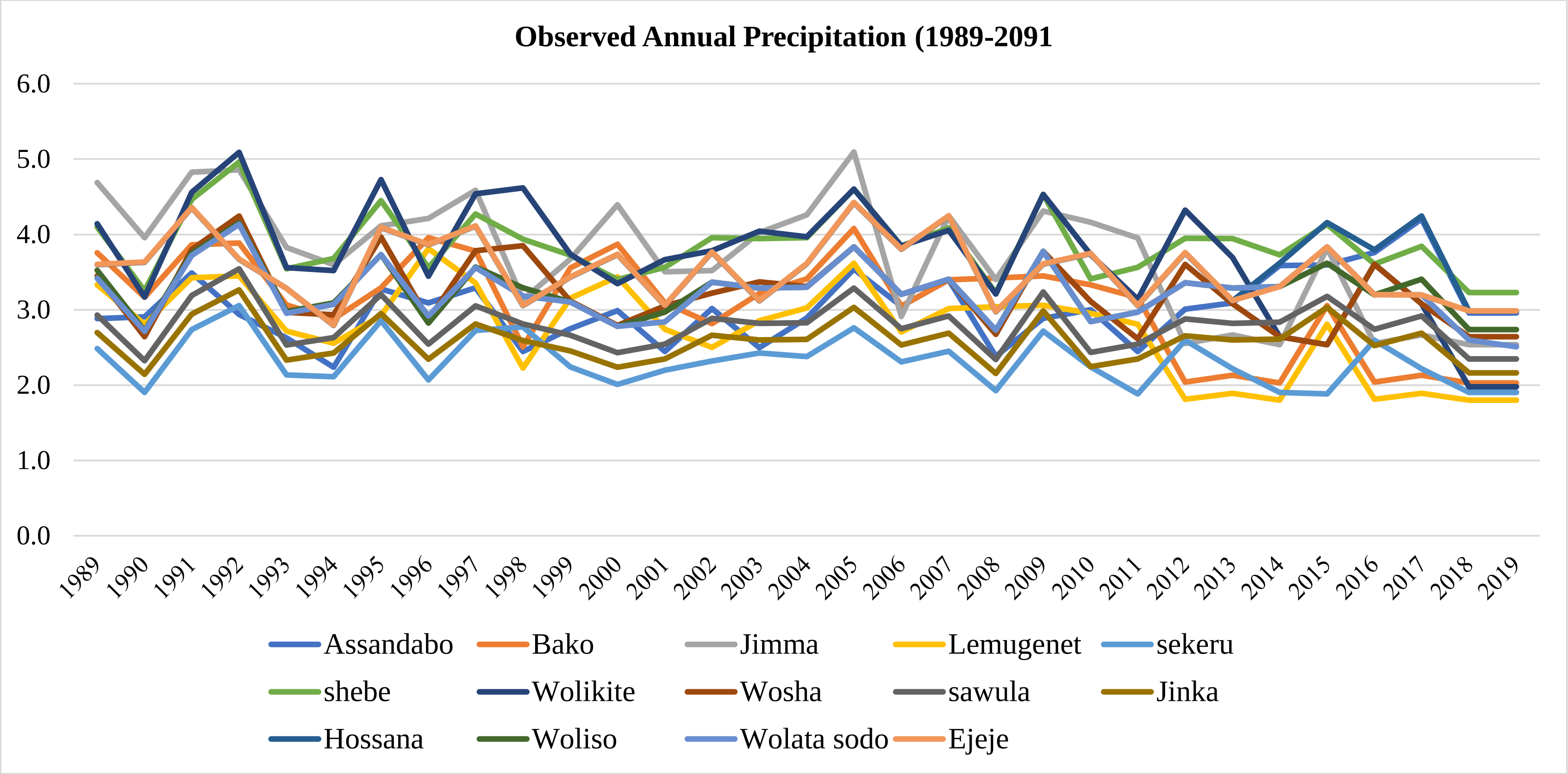
APPENDIX 8d: Observed Annual Precipitation



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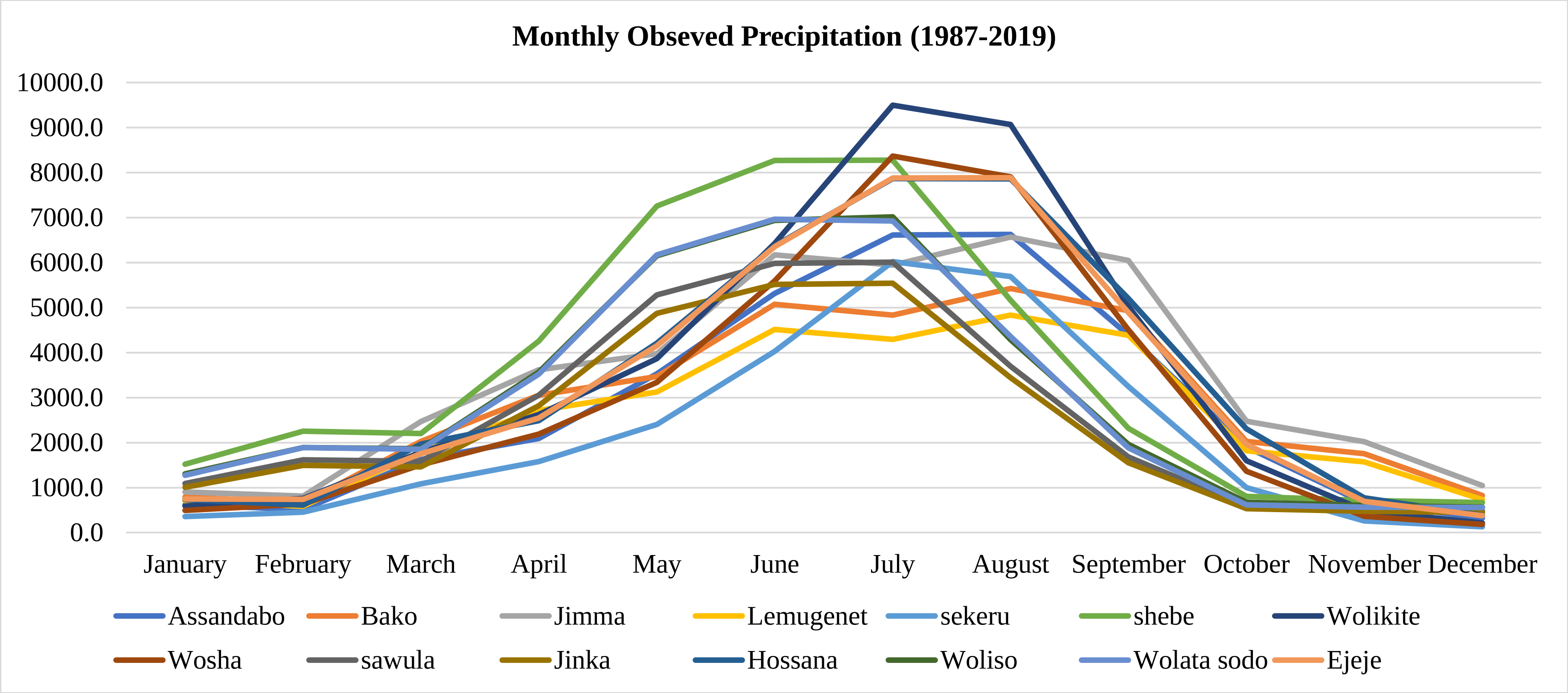
APPENDIX 8e: Observed Monthly Precipitation



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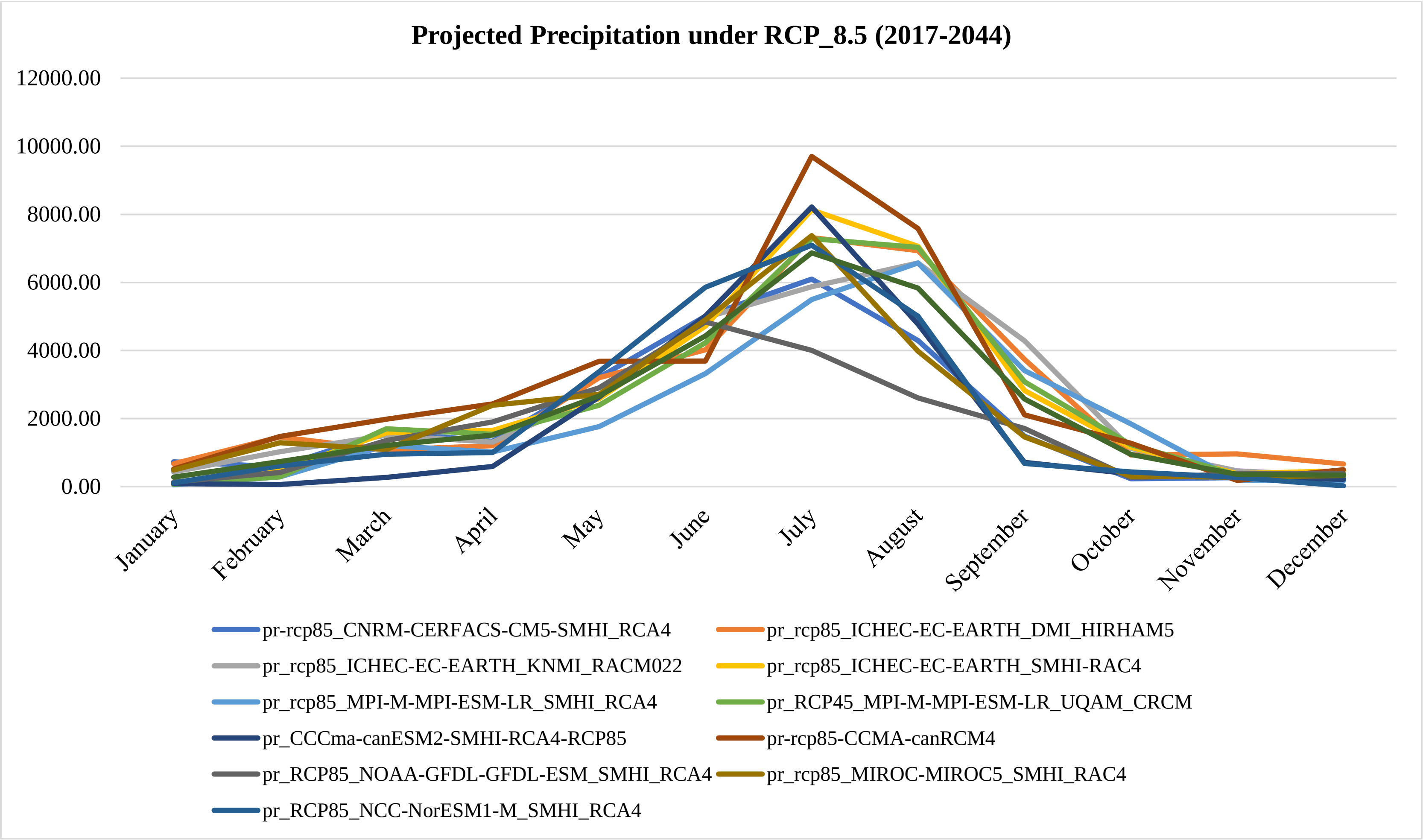
APPENDIX 9: Projected Temperature and Precipitation

APPENDIX 9a: Projected Precipitation



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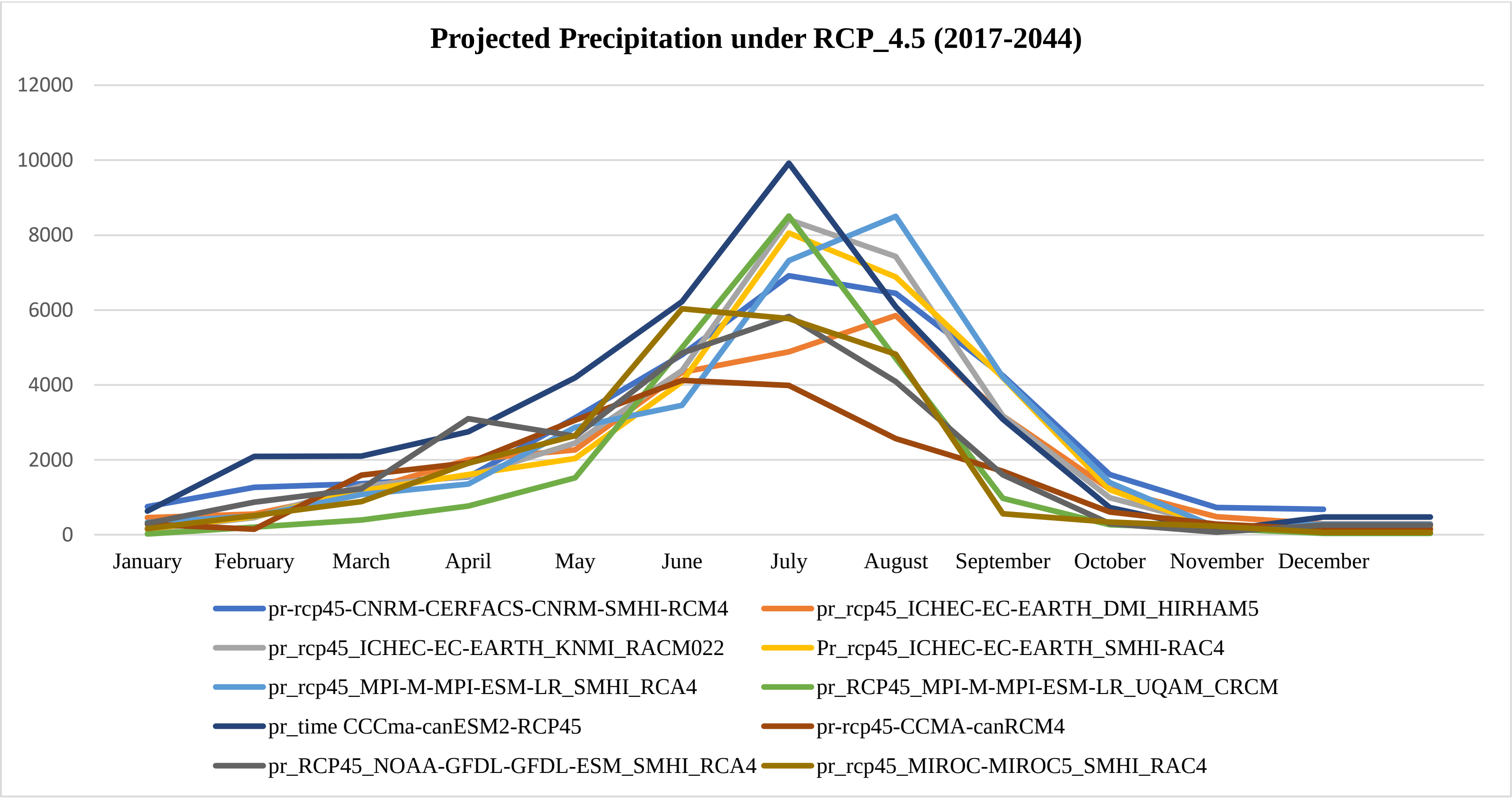
APPENDIX 9b: Projected Precipitation



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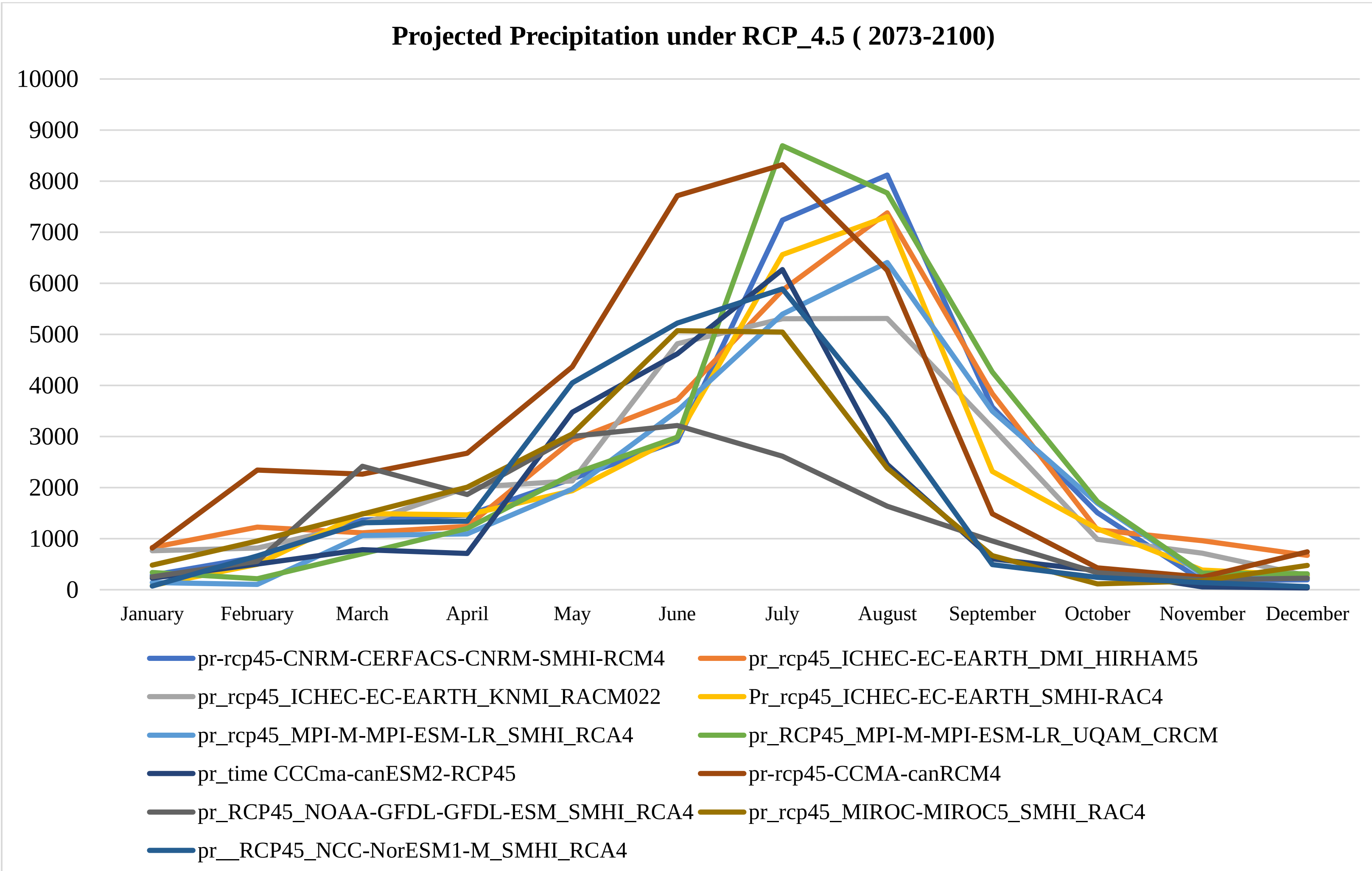
APPENDIX 9c: Projected Precipitation



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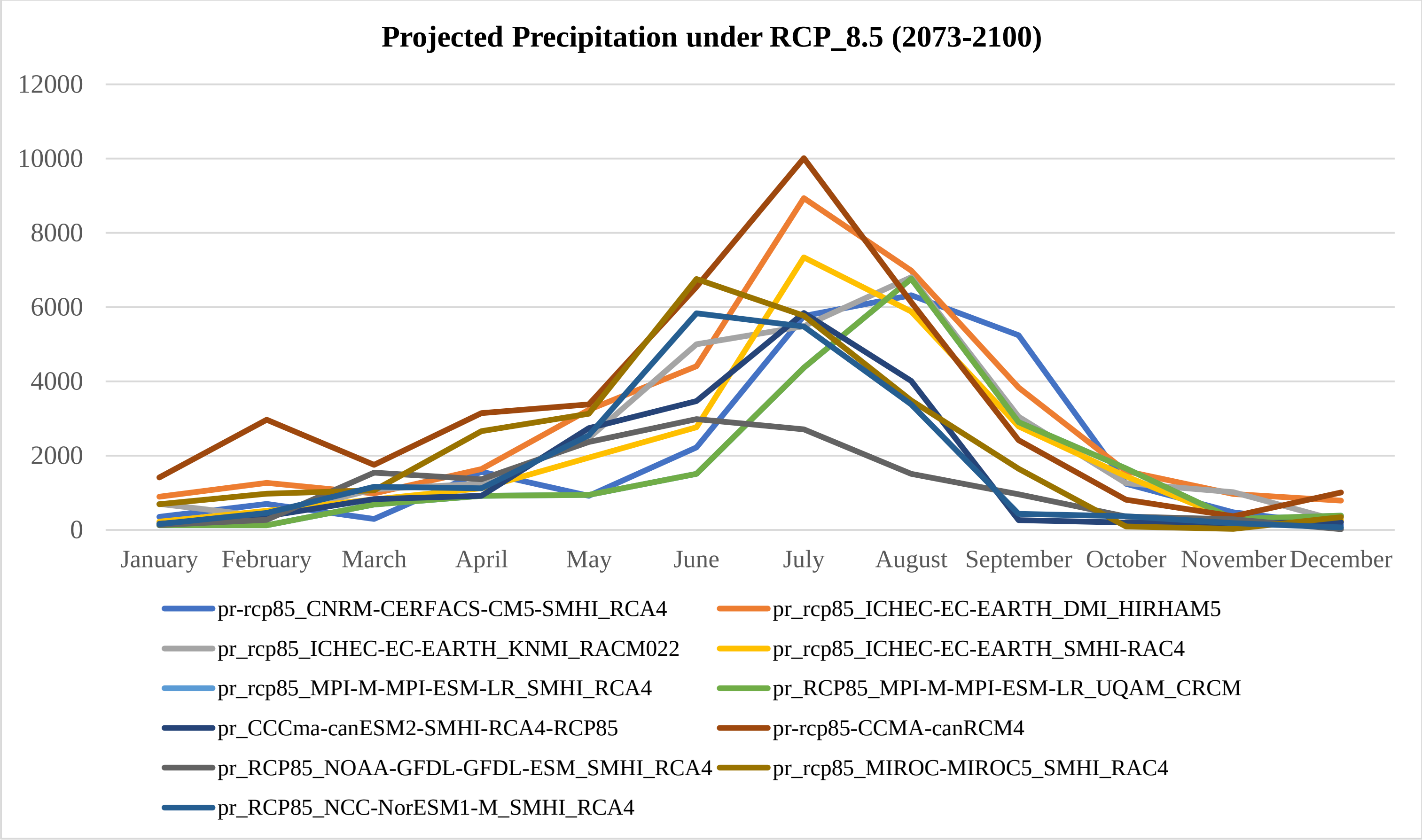
APPENDIX 9d: Projected Precipitation



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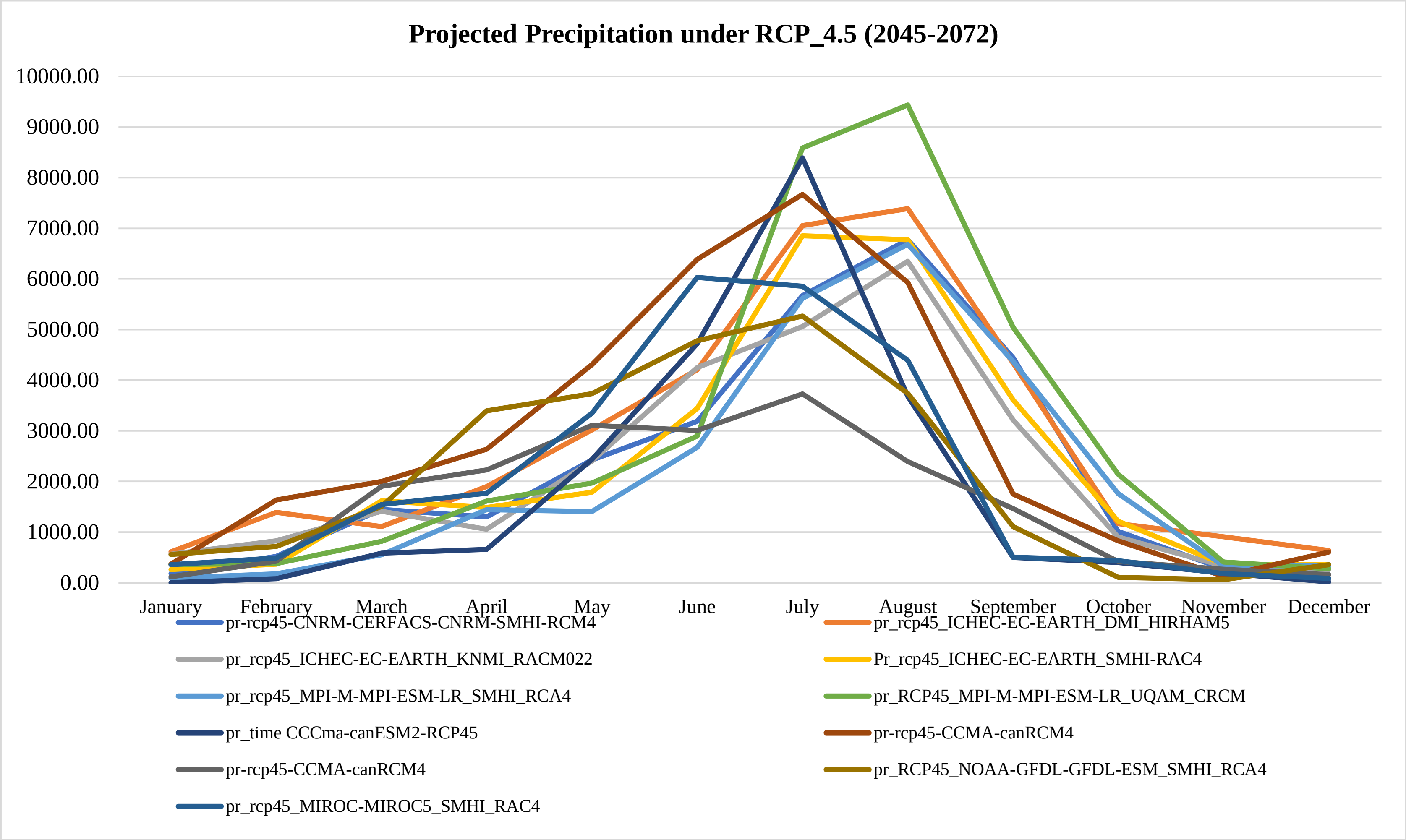
APPENDIX 9e: Projected Precipitation



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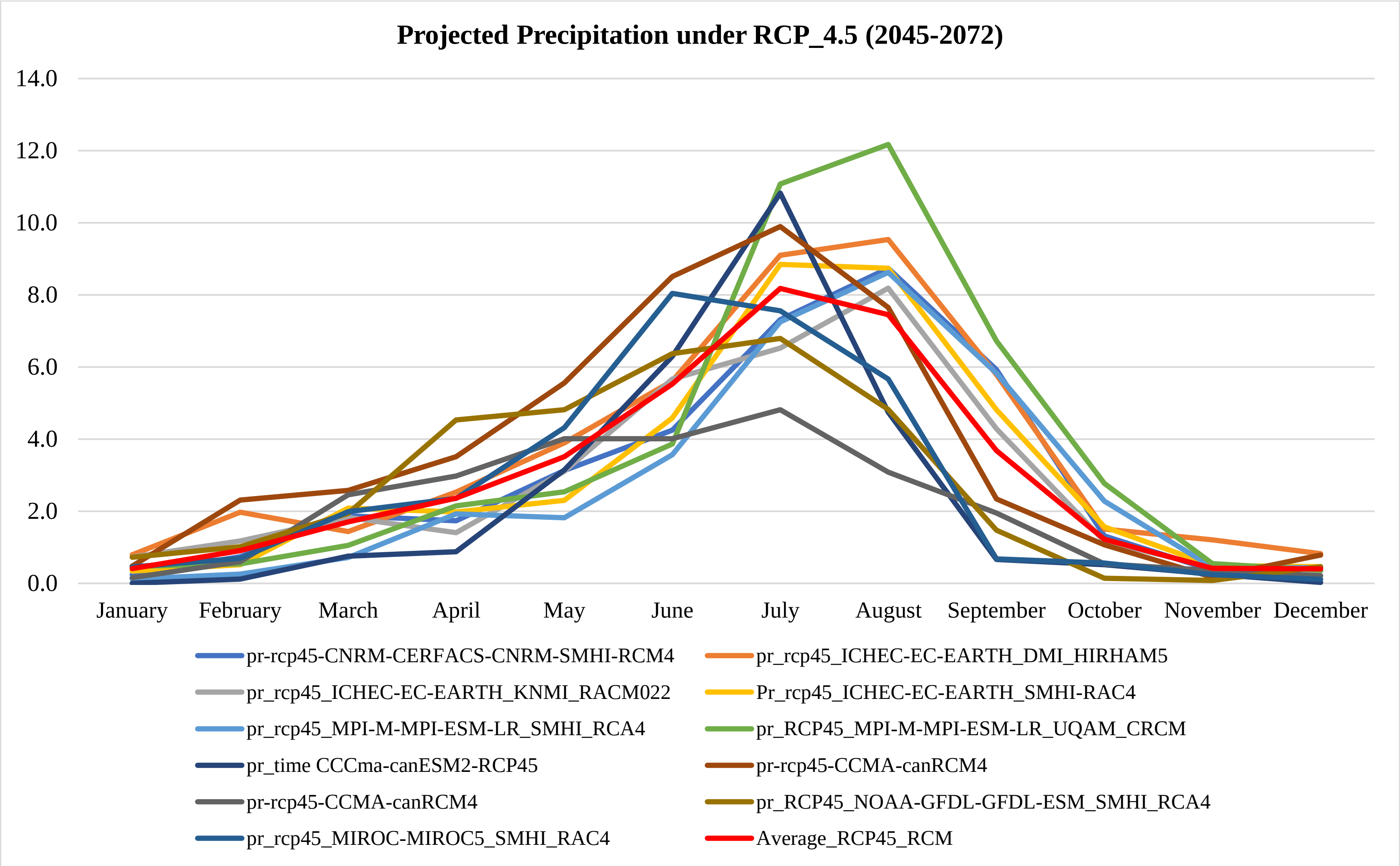
APPENDIX 9f: Projected Precipitation



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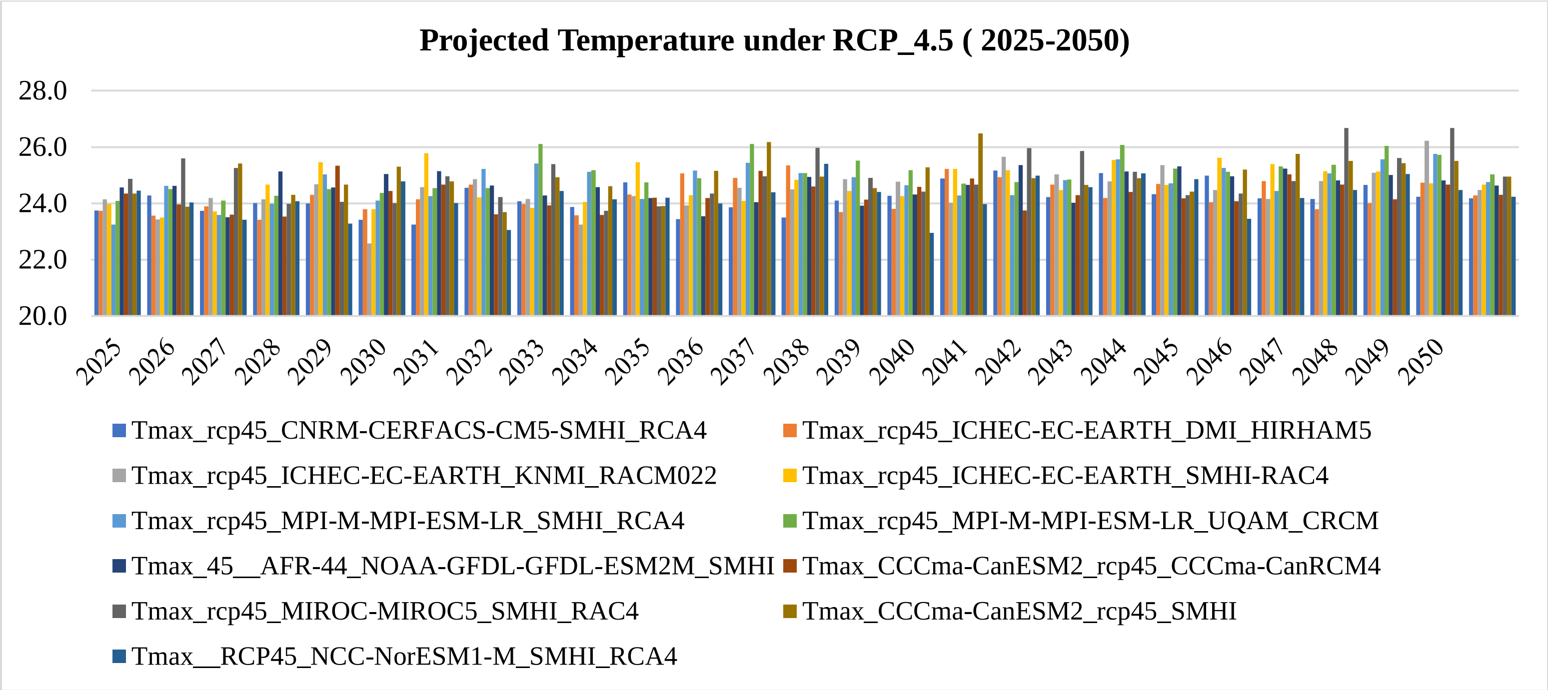
APPENDIX 9g: Projected Temperature



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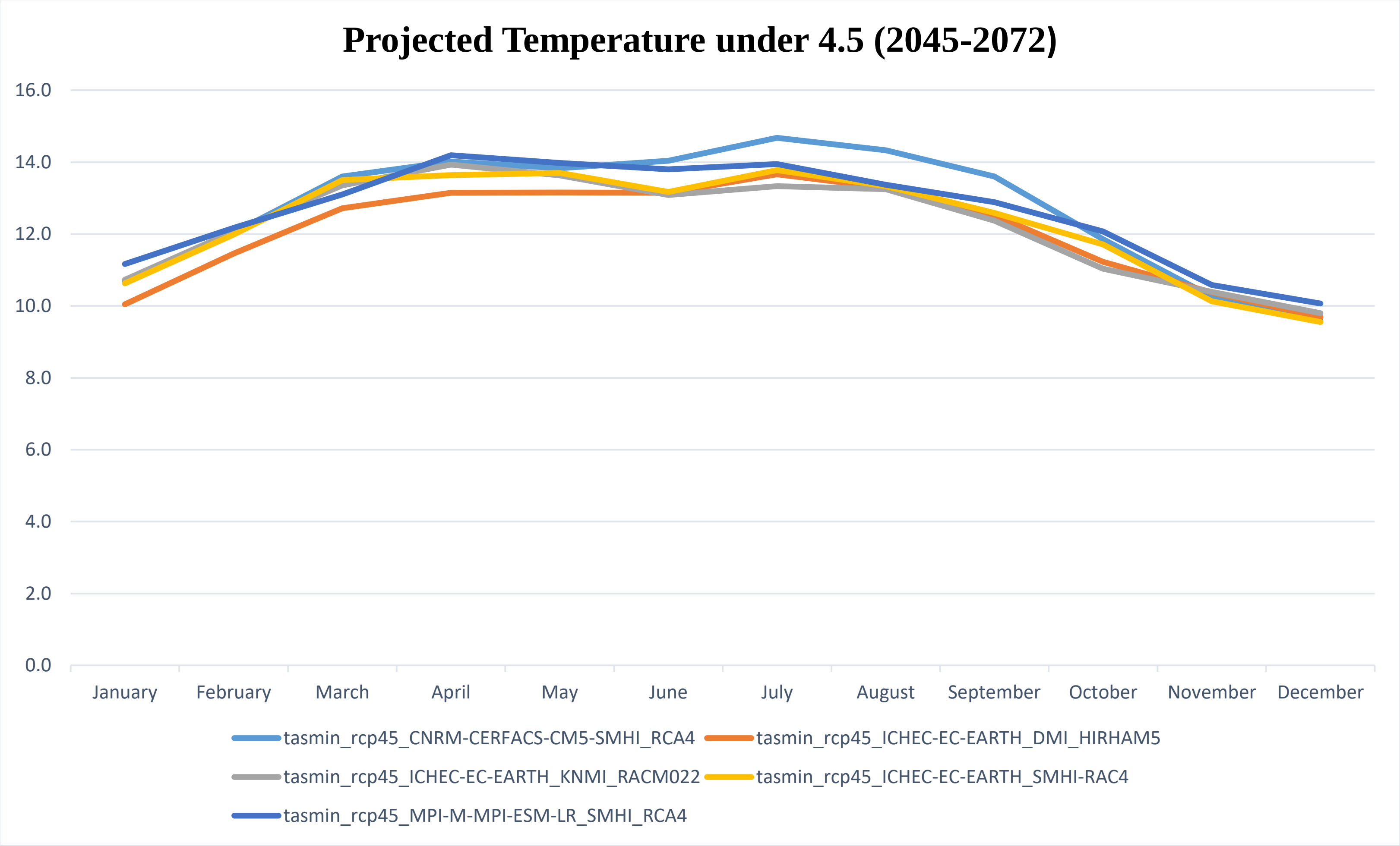
APPENDIX 9h: Projected Temperature



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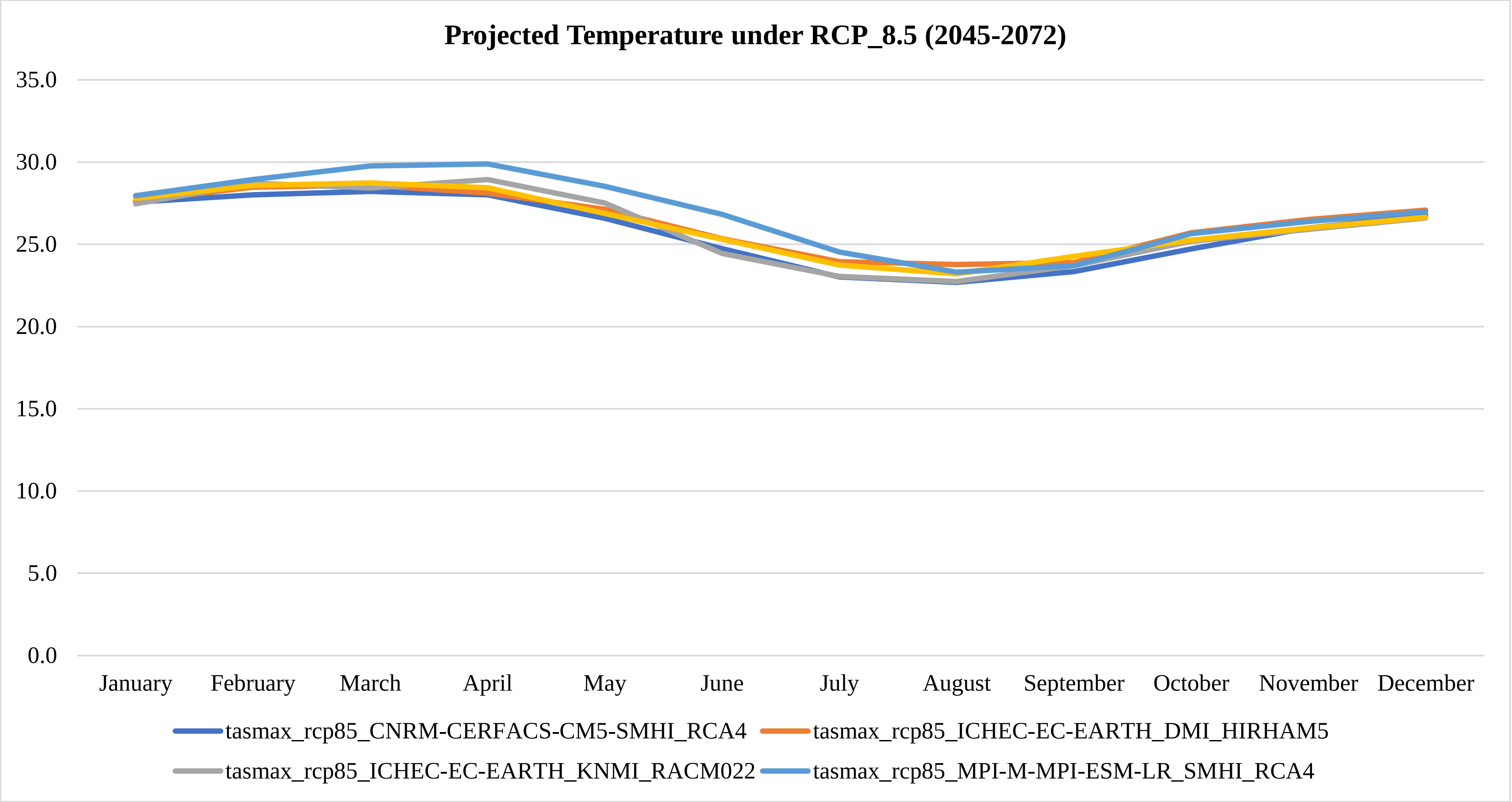
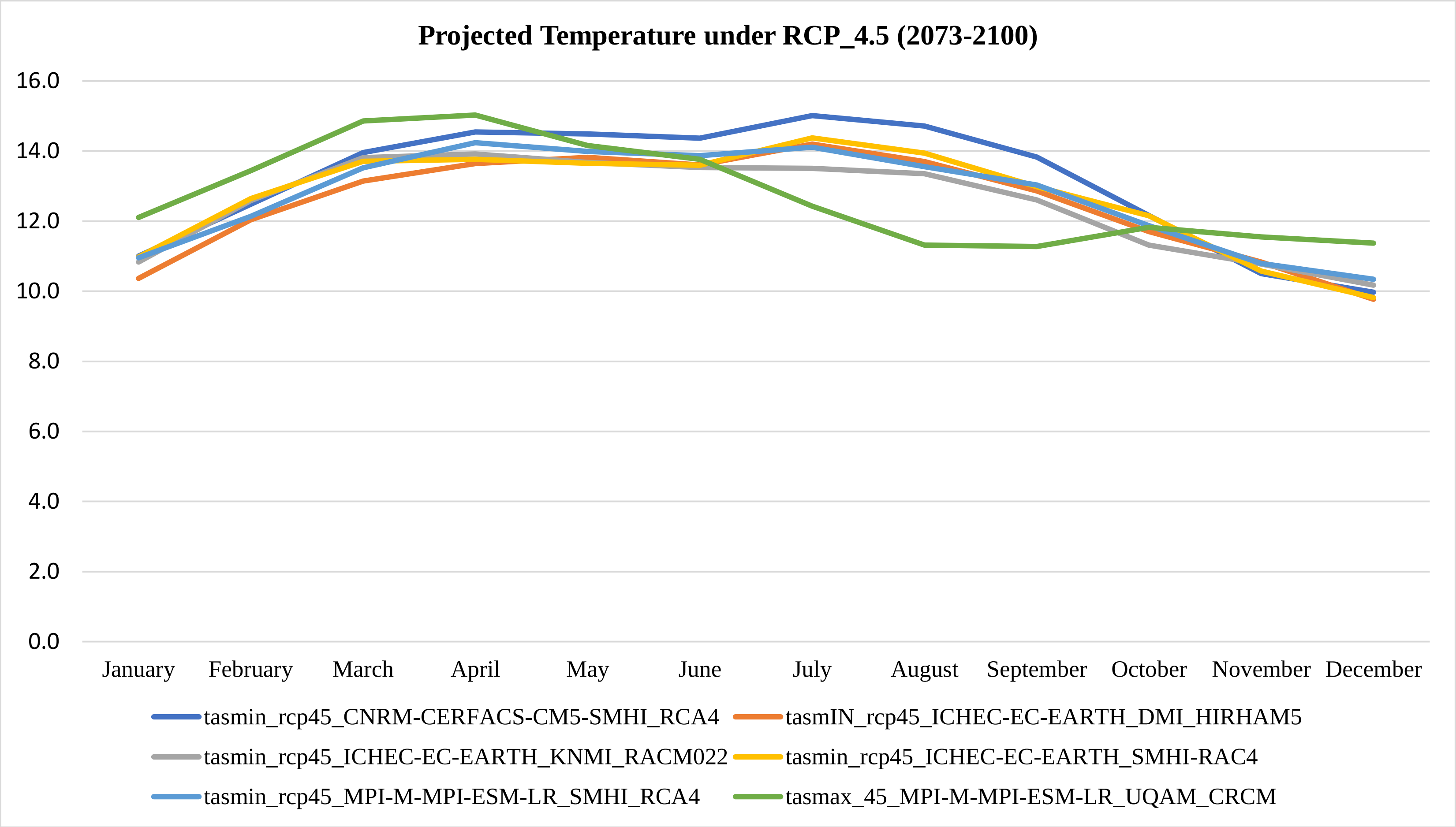
APPENDIX 9i: Projected Temperature



APPENDIX 9j Projected Temperature



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